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THESIS

ANALYSIS OF DETERMINANTS OF STUDENT PILOT SUCCESS FOR UNITED STATES NAVAL ACADEMY GRADUATES

by

Anna E. Boyd

June 2003

Thesis Co-Advisors: William R. Bowman
Janice H. Laurence

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The purpose of this study is to determine which characteristics and outcomes that are measured/determined at the Naval Academy serve as the best predictors of attrition from naval pilot training before or during the Primary phase, as well as performance in the first two stages of training: the academic portion of Aviation Preflight Indoctrination (API) and the flying portion of Primary phase. The reason for this is twofold; 1.) to examine the current aviation assignment policy at the Naval Academy (predominantly based on ASTB and OOM) to determine if it is significantly related to pilot performance (academic, flying and attrition) in flight school, and 2.) to examine alternative criteria to determine the possibility of developing a more effective model for predicting performance.

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ANALYSIS OF DETERMINANTS OF STUDENT PILOT SUCCESS FOR UNITED STATES NAVAL ACADEMY GRADUATES

Anna E. Boyd
Lieutenant, United States Navy
B.S., United States Naval Academy, 1996

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Author: Anna E. Boyd

Approved by: William R. Bowman, Ph.D.
Thesis Co-Advisor

Janice H. Laurence, Ph.D.
Thesis Co-Advisor

Douglas A. Brook, Ph.D.
Dean, Graduate School of Business and Public Policy

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ABSTRACT

The purpose of this study is to determine which characteristics and outcomes that are measured/determined at the Naval Academy serve as the best predictors of attrition from naval pilot training before or during the Primary phase, as well as performance in the first two stages of training: the academic portion of Aviation Preflight Indoctrination (API) and the flying portion of Primary phase. The reason for this is twofold; 1.) to examine the current aviation assignment policy at the Naval Academy (predominantly based on Aviation Selection Test Battery and Order of Merit) to determine if it is significantly related to pilot performance (academic, flying and attrition) in flight school, and 2.) to examine alternative criteria to determine the possibility of developing a more effective model for predicting performance.

To test the hypotheses, multiple regressions will be run on each dependant variable. First will be a linear regression to test for predictors of academic performance in API. The dependant variable will be raw API final grade (NASCRAW). Second will be a linear regression to test for predictors of flying performance in the Primary phase of training. The dependant variable for this regression will be raw Primary flight grade (PFG). Third and finally will be a logistic regression to test for predictors of attrition before or during the Primary phase of training, and the dependant variable for this test will be Primary attrite (PRI_ATTR).

Though the specific variables that predict performance vary by criterion, it is clear that using additional variables beyond just OOM, ASTB and an interview offer a broader picture of flight school performance. If predicting the entire package is the goal, then in two tests of three (API and attrition) the alternate variables should be used and in the third (Primary flight grades) both methods yield the same results. At no point did the current method of selection have a greater predictive impact than the alternate variables.

Although these results indicate that the current method for selecting individuals for pilot flight school is certainly adequate, it is clear from the analysis that, in general, there are other variables that could better predict these outcomes.

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I. INTRODUCTION

For any organization to be successful, it must be able to identify the characteristics in people that are best suited for the job (Carretta & Ree, 2000). One facet of success is cost effectiveness, and training Naval aviators is a costly endeavor. On the high end, the finished product -- a winged Naval Aviator -- costs U.S. taxpayers approximately $1,500,000 (Naval Education and Training Professional Development and Technology Center, Analysis and Costing Branch, FY02 cost-to-train data). The Navy estimates the cost of each pilot-hopeful who fails out of pilot training to be between $20,000 and $160,000, depending on stage and pipeline[1]. If a student fails to achieve wings, he or she has not only cost the Navy, and therefore taxpayers, money, but has also been a personnel drain on the Navy while in flight school. Because the Navy does not possess an over abundance of money or personnel, it is crucial to streamline the selection process to maximize the candidate-to-winged aviator ratio and minimize attrition. It is in the best interest of the Navy to know what characteristics make a quality pilot, and find the people possessing those characteristics to fill the billets available, in order to reduce training cost (i.e. attrition and requirements) and increase organizational efficiency and effectiveness. It does the Navy a disservice to use a potentially deficient means for selection if there are better possibilities available. This study will examine the aviation service assignment process at the United States Naval Academy (USNA) and attempt to determine if it is the best method available or if there are alternatives that could prove more effective in predicting training performance and attrition.

A. BACKGROUND

Throughout the history of aviation there have been three primary "theoretical areas" as well as three "measurement thrusts" (Hilton & Dolgin, 1991, p. 81) that have dominated the process of pilot selection. The theoretical areas are: intelligence, personality, and psychomotor ability, and the measurement thrusts are apparatus tests, paper-and-pencil tests, and observation/interviews. Studies show that in the past century

[1] Stage refers to the stage of training. These are Aviation Preflight Indoctrination, Primary, Intermediate and Advanced. Pipeline refers to the different specialties pilots are divided into after Primary; they are jet, propeller, or helicopter.

there have been blocks of time (usually book-ended by significant events such as world wars) where one or another of each type was emphasized over the others. In the early years, self selection was the primary means of gaining entry into the world of aviation. When the military took up flying, rigorous medical screenings were responsible for eliminating a great deal of pilot-hopefuls. During World War I, even with the rigorous medical exams, the numbers that would voluntarily quit or would fail out of training were still unacceptably high so the Committee on Psychological Problems of Aviation was formed.

Because the aircraft became more complex and the role of a pilot expanded beyond that of just manipulating flight controls, the emphasis on intelligence as a selection criterion increased over the years. However, it was recognized that this emphasis on intelligence was focused more on an aptitude for flying that in "book smarts." At first a college education in and of itself was considered a sufficient measure of intelligence, however it was realized later that there was "no compelling evidence that educational achievement beyond high school creates better military pilots" (Hilton & Dolgin, 1991, p. 94) at the same time recognizing the fact that "above average intelligence is required to master military pilot training" (Hilton & Dolgin, 1991, p. 94).

It was and is still universally accepted that flying military aircraft demands a level head and courage. Likewise, a pilot must exhibit certain personality traits, such as maturity, good judgment and motivation. There has been a search for the abstract, difficult to measure, "right stuff" that a pilot must possess, though this quality remains empirically elusive.

Psychomotor ability bridges the gap between the theoretical and measurement areas. Clearly, flying requires a degree of coordination to think and react at the same time, sometimes independent of one another. Apparatus tests have evolved from the earliest tests of covering an individual's eyes then spinning them around in a chair. These tests were conducted to test for propensity towards dizziness, blackout, or motion sickness, all considered disqualifying. During World War II, stick and rudder tests were

developed to test eye-hand-foot coordination (Hilton & Dolgin, 1991, p. 83, 90). In the 1960s dichotic listening tests[2] were introduced.

The first paper-and-pencil tests used in aviation were intended solely to test intelligence. As they evolved over the years they have come to include tests for mechanical comprehension, personality traits, and spatial awareness. Though the Navy currently relies heavily on paper-and-pencil testing (in the form of the Aviation selection Test Battery, or ASTB) to predict aviation training performance, studies have shown that apparatus tests are generally better predictors of job performance (Grant, 1980 in Hilton & Dolgin, 1991). It would follow, then, that apparatus tests would likewise be better predictors of pilot performance.

Interviews have always been geared to measure motivation at the least, and often included measures of emotional stability, maturity and pilot potential (Hilton & Dolgin, 1991, p. 84, 87). In addition to psychological testing, interviews have also been used to measure for the so called "right stuff."

Clearly the military has been conducting studies on predictors of aviation performance and measurements since WWI (Carretta, 2000). Most often the criteria used have been some combination of cognitive ability (as measured by standardized tests, college grades, and major), medical/physical qualification, prior flying experience, and "officership" (military performance) (Carretta, 2000). There is no denying that a certain level of intelligence is required to be a competent and effective aviator. Flying demands more than being able to take off and land safely and understanding the basic principals of flight. More often than not, flying involves a great deal of multitasking in the cockpit, including the physical aspect of flying, navigating from one place to the next, understanding the information the cockpit instruments are giving, communicating with air traffic controllers and other aircraft, and ensuring the aircraft is operating properly (Pohlman & Fletcher, 1999). If the situation is not ideal, a pilot may also be managing a

2 Dichotic listening – individual being tested has a different sound input of letters and numbers presented to each ear over headphones and must concentrate to extract the information required and record it on a keypad.

deteriorating weather situation or attempting to diagnose and fix or at least mitigate an aircraft malfunction. Much of this requires an exceptional level of good judgment and a cool head under pressure.

It has been said that there is "no other occupation in the world that benefits more from personnel selection technology than that of military pilot" (Hilton and Dolgin, 1991, p. 81). Above and beyond the requirements of civil aviation, military pilots must take on an added workload. They must manage the extra stresses of understanding and employing weapons systems, know and adhere to Rules Of Engagement, deal in a dynamic combat environment and in the Navy, take off and land on an inherently unstable platform a fraction of the size to which most pilots are accustomed.

Clearly there are many different aspects to being a competent aviator, many of which are not academic, and are difficult to measure. A multitude of studies over nearly a century have attempted to pinpoint exactly what measurable trait or combination of traits are most important in selecting people to train as aviators (Hilton & Dolgin, 1991, Carretta, 1992, Pohlman & Fletcher, 1999, Carretta, 2000, Carretta & Ree, 2000, Weeks, 2000). This thesis will review many of the previously examined variables as well as others in detail and attempt to determine the strengths and weaknesses of each.

1. Aviation Selection Process

Accurate prediction of pilot performance is an ongoing endeavor by all branches of the Armed Forces (Carretta, 1987; Reinhart, 1998). Though aviators come from all commissioning sources, this thesis will focus predominantly on those that come from the U.S. Naval Academy and the process by which they are chosen. Each year the Navy's Officer Plans and Policy branch allocates a certain number of billets to be filled by USNA, based on needs of the Navy. For the years covered in this study (1995-1998) there were 209/232/243/250 pilot billets respectively. The Naval Academy decides internally how to distribute the billets it receives. Thus far there have been several different equations used, all of which have incorporated Order of Merit (class rank) as a central criteria. To date there have been at least two different methods of assigning billets at the U.S. Naval Academy. Until 1994, midshipmen would line up on "Service Selection Night" in numerical (Order Of Merit, OOM) order and as their numbers were

called they would have the opportunity to select from whatever warfare options were available. Logically, the early numbers had freedom to select whatever profession they wanted, but the later numbers got what was left (Chief of Naval Operations, 1994). In 1995, "service selection" became "service assignment" and instead of basing the procedure entirely on Order of Merit an interview process was added. The goal of the interview is to provide additional information to the assignment board and serve as a "reliable indicator of a midshipman's suitability for commissioning and for a particular community" (Aviation Service Assignment Multiple brief, 2002).

In general (not USNA specific) the process for application for naval aviation training begins with taking the Aviation Selection Test Battery (ASTB). Approximately 50% of applicants are eliminated at this point for not meeting the minimum test standards. Of those that meet the minimum requirements, approximately 25% will be found not physically qualified (NPQed) by the rigorous medical/physical screening (Williams et. al, 1999). Those that are able to achieve the minimum required scores on the ASTB and are found physically qualified then undergo an interview; the results of which are forwarded to an evaluation board.

At USNA this interview is conducted by a panel of two to three officers; the senior ranking officer is an aviator and the remaining can be from any warfare specialty. The midshipman interviewee is graded on a scale of 0 to 10 in five areas; "appearance and poise; oral communication and expression of ideas; leadership potential; community motivation; and community understanding" (Commandant of Midshipmen, 2002, p. 2). Additionally, each interview panel provides written comments. The interview score is combined with ASTB score and Order of Merit in a 10%/25%/65% ratio. From this a Service Assignment Multiple (SAM) is derived and midshipmen Service Assignment packages are reviewed by the Service Assignment Board in SAM order. SAM only determines the order in which the packages are reviewed; it places no precedence on the order in which billets are assigned.

After the Service Assignment Board reviews each package and makes its choice of who will be assigned aviation billets, the list of recommended assignments is

forwarded to an Executive Review Board to be reviewed for precept compliance.[3] Finally, the Executive Review Board forwards the list to the Superintendent for final decision (Chief of Naval Operations 1995; Superintendent, U.S. Naval Academy, 2002). On Service Assignment Night, midshipmen are told what they have been assigned, rather that selecting at that point what they want as was done in previous years. Ultimately, only approximately 15% of naval aviation hopefuls pass all of the requirements to begin flight training (Williams et. al, 1999).

In reality the interview process at USNA only effects a midshipman's overall standing from OOM to SAM if they are on the cutoff for a particular community (United States Naval Academy Department of Professional Programs, 2002). For the USNA class of 2002, only 2 people moved greater than seven positions, and 174 moved three positions or less. Additionally, the midshipmen know the basic interview questions prior to the interview, therefore allowing for rehearsed responses and virtually eliminating any spontaneity.

According to USNA Instruction 1531.51A (1996), Order of Merit is essentially the same as class rank and is made up of several criteria. Academic and military classes[4] make up the majority of it (64.48%), followed by military performance (17.68%), conduct (7.8%), physical education (6.66%) and finally athletic performance (3.38%).

2. Naval Aviation Training

Flight school is made up of four stages of training. The first stage is Aviation Preflight Indoctrination (API) which is approximately one month of academics interspersed with physical training as well as land and water survival and aviation physiology. API is "designed to provide commissioned officers of the United States Uniformed Services and selected International Military Students with the basic skills and knowledge needed for Primary Pilot and Naval Flight Officer (NFO) Training (Naval Aviation Schools Command, 2001, pg. vii). Successful completion of API is required prior to reporting to one of the Primary Flight Training squadrons. The academic portion

[3] The precept is promulgated by the Superintendent and sets the guide for the service assignment review boards.

[4] Military professional classes (leadership, seamanship and navigation, etc.) comprise approximately 18%, or one course per semester, of a midshipman's course load.

includes classes in Aerodynamics, Aviation Weather, Aircraft Engines and Systems, Air Navigation, and Flight Rules and Regulations. Each course has one final exam except for Aerodynamics which has a midterm and final. The exams are written by the instructors and are reviewed every six months for revisions. Each test has approximately 50 questions and 80% is required to pass.

API is the only course of training that is identical for pilots and NFOs. Following API, the majority of pilots report to either Whiting Field, FL or Corpus Christi, TX for Primary Flight Training while a small handful will go to Vance Air Force Base in Oklahoma to train with the Air Force. NFOs go through Primary Flight Training at Naval Air Station Pensacola.

Primary Flight Training consists of both an academic and flying (actual aircraft or simulator) evaluation. It is roughly 19 weeks in duration, with approximately 120 hours of ground school (including seven exams), 20 hours in the simulator, and 70 hours of flight time (Chief of Naval Air Training, 2002). Each flight and simulator has a grade sheet outlining the minimum criteria to be evaluated on the flight, and each criterion is graded on a four point scale. Grades are determined as follows: Unsatisfactory (1.0) indicates that the student is not ready to proceed to the next stage of training. Below Average (2.0) indicates that the student meets the minimum requirements to move on, but is below performance standards. Average (3.0) means the student is ready to proceed and meets performance standards. Above Average (4.0) signifies the student is ready to proceed and exceeds performance standards. Additionally, each academic, flight and simulator event is graded overall as Satisfactory or Unsatisfactory. A grade of Unsatisfactory can result from: 1) inadequate preparation for an event (flight or simulator) displayed prior to the event ("ready room down"), 2) failure of an academic test, 3) a grade of unsatisfactory on any of the graded criteria of a flight/simulator, 4) demonstrated lack of motivation during an event, 5) end-of-phase unsatisfactory.[5]

[5] End-of-phase unsatisfactory is defined as a final grade greater than 1.5 standard deviations below squadron average in Primary Phase Training.

All pilots complete identical[6] Primary Flight training at the culmination of which they are divided among the different pilot pipelines (jet, propeller, helicopter) based on their grades, personal preferences, and needs of the Navy for the remainder of pilot training in the Intermediate and Advanced Stages.

B. PURPOSE

As described earlier in this chapter, ASTB and OOM are the predominant measures for determining aviation assignment from the Naval Academy. While this has thus far proven an adequate method for assigning billets, it has never been determined conclusively to be related significantly to successful completion of flight training. This study will examine its efficacy and, in addition, identify alternative characteristics of Naval Academy graduates that may also predict success in, as well as attrition from, flight training. The ultimate goal is to determine if there exists a possible, more predictive, alternative to the current method used. Because flight training comprises more than just flying, this study will focus on the academic portion of Aviation Preflight Indoctrination, and the flying portion of Primary phase training, examining what criteria are predictive of performance in each and if the criteria are the same in each. Additionally this study will examine attrition during or before the Primary phase and attempt to determine what criteria can be used to determine the likelihood of it occurring. The results of this research will benefit the U.S. Naval Academy and support the goal of sending the highest quality graduates through the Naval Aviation training pipeline, thereby reducing wasted training time and funds, and improving the operational standard in the fleet.

C. RESEARCH QUESTIONS AND METHODOLOGY

The primary goal of this research is to determine if the U.S. Naval Academy is using all relevant information for determining who will undergo Navy pilot training. To accomplish this task, the first step will be to review previous research on the topic and related topics. Following a thorough literature review all variables will be examined and correlated with flight school performance (in the form of API academic grades and Primary phase flight grades) and attrition results to determine which variables best

[6] Pilots who train with the Navy at Whiting Field or Corpus Christi follow the same syllabus; those that train at Vance Air Force Base follow an Air Force designed syllabus.

predict a high level of performance in training and a likelihood of attrition. Demographics (gender and ethnicity) will be included as controls, and the primary criteria to be examined will be Aviation Selection Test Battery (ASTB) scores and OOM inititally, then additional performance variables as measured by academic and military grades, and finally major selection and grades-in-major interaction.

D. SCOPE AND LIMITATIONS

The scope of this study will concentrate on U.S. Naval Academy graduates from the graduating classes of 1995 through 1998 who were assigned as Navy and Marine pilots. To suit the purpose of this study, only U.S. Naval Academy graduates are being included. Only the classes of 1995 through 1998 are being studied because these classes all came by their career path through the same process (service assignment rather than service selection), they were not affected by decisions made surrounding the combat exclusion clause[7] or elective eye surgery[8], and these classes make up the most robust data from the Chief of Naval Air Training (CNATRA) database. In order to better concentrate the focus of the study, only pilots will be included.

Motivation has been argued by some to be one of the most important criteria influencing an individual's performance in flight school. However, this research is limited in that a direct measure of motivation is not available. Likewise, there are other factors that can and will affect one's performance. Recently it has been mandated that all aviation selectees receive 40 hours of flying lessons prior to arriving in Pensacola. Previously there were some individuals who obtained private flying lessons on their own, some of whom achieved multiple flight ratings. This could be attributed to motivation, and could as well contribute to flying performance once they arrived in Pensacola.

As with any research, there is no way to ensure the data used here are uncontaminated or without deficiency. It was gathered by humans and is therefore subject to some degree of human error. Finally, there are two factors at work here that

[7] Prior to service selection for the class of 1994, due to the combat exclusion clause preventing women from serving in combat, women were able to select restricted line billets. With the lift of the combat exclusion clause the requirements for women were made the same as for men, and those that were "Physically Qualified" were required to select unrestricted line jobs.

[8] Prior to 2002 aviation hopefuls were not permitted to have elective eye surgery (Photorefractive Keratectomy, or PRK) in order to perfect their vision to meet pilot selection requirements.

cannot be controlled for: human nature and subjective grading. Though every effort is made to attempt to keep everyone on a level playing field when it comes to comparing an individual's performance to a standard, to assure that everyone is compared fairly and treated equally is nearly impossible. Accepting all of these factors as limitations, this research will be as thorough and representative as possible under the circumstances.

E. ORGANIZATION OF STUDY

The plan of this thesis is as follows: Chapter II will provide an overview of past research on this topic as well as related research, Chapter III will discuss the data to be used, define the variables and make the hypotheses, Chapter IV will provide preliminary analysis, develop the theoretical and statistical models to be run, and give results of the analysis, and finally, Chapter V will give the summary, conclusions and recommendations for future research.

II. LITERATURE REVIEW

A. CONTRIBUTING FACTORS

There are numerous factors that contribute to one's success or failure in training and on the job. These factors can range anywhere from ability (which in and of itself can be further broken down into subcategories) to zeal and include everything in between. Pilot selection methods have varied over the years but have generally placed emphasis on physical/medical qualification, cognitive ability, instrument and mechanical comprehension (as gauged through selection tests), psychomotor coordination, and often some limited in-flight performance. For this study, concentration will be placed primarily on the personnel characteristics and outcomes at the Naval Academy as predictors of aviation training performance.

1. Gender

Gender differences in job performance have been a subject of debate for as long as women have fought for equality in employment. Though there are those that attest that "women have no place in an equal working environment with men," studies show that even in previously male-dominated professions gender differences in job performance are likely due to inequality in levels of employment, promotion opportunity, and income (Harrison & Rainer, 1997). Another possibility is that "preconceived notions about men and women may influence the evaluation process" (Hartman, et al., 2001, p. 452). In other words, if a woman's performance in a predominantly male environment is being evaluated; personal biases may come into play. Interestingly, though, these biases are not always negative. Some studies have shown that women's performance is sometimes overrated as compared to men's, if good performance was unexpected (Hartman, et. al., 2001). If a woman is not expected to do well and does, the resulting performance rating may actually be higher than if a man had performed at the same level. Thus far, few studies have researched gender differences in specific job-related tasks. Military pay scales guarantee equal pay for equal rank. This policy, together with the push towards gender equality in the military and the lifting of the combat exclusion clause, has put women, for the most part, on an even footing with men when it comes to job availability

and income. This being said there are most likely still gender related job performance differences. The combat exclusion clause was lifted only in the last decade; therefore women have not had much time to make up for differences in experience over that amount of time. Discrimination, though latent, still exists, and may also have an influence on these differences.

Between 1990 and 1997, the numbers of female pilots in military aviation increased only slightly (even with the lift of the combat exclusion clause) from 364 to 380 (Office of the Under Secretary of Defense Personnel and Readiness, 1999). One might explain this phenomenon by the across-the-board drawdown of the military, but their percentage of all pilots only increased by .5% (1.5% to 2.0%) in that amount of time.

Women entered Naval Aviation as pilots in 1973 and as Naval Flight Officers in 1979. Aviation psychologists have conducted numerous studies on the effects of women in aviation. In 1992, a study was conducted examining the gender differences on selection tests, preflight training grades, and attrition. Interestingly enough, the results of the study showed women scored significantly better on the selection tests designed to predict preflight academic performance (Academic Qualification Test, AQT), but subsequently performed significantly lower in the preflight academic training that the selection tests are designed to predict (Baisden, 1992). This study also found that men scored significantly higher on the test designed to predict flying performance (Flight Aptitude Rating, FAR). Additionally, differences in attrition rates and reasons for attrition were not statistically significant. Hafner (2000) in his study on Naval Flight Officer performance concluded that gender was not a significant predictor of completing flight training. Additionally, Reinhart (1998) found no statistical significance between gender and primary flight school grades for pilots.

2. Cognitive Ability

There is a school of thought that "g" or general cognitive ability, is the most important ability a person possesses and therefore is accurately predictive of other things, namely job performance (Ree & Earles, 1992). By this logic, an individual's job performance, regardless of the job, can be predicted, almost entirely, by an intelligence

test. Critics of this school of thought assert that practical intelligence has a place along side academic intelligence in predicting performance (Sternberg & Wagner, 1993). The reasons cited stem from the differences in the problems presented. Academic questions are well defined, present all information required to solve the problem, and have only one correct answer. Whereas practical problems often need at first to be recognized as a problem, are incomplete in the information presented, may require experience and motivation to solve, and may have more than one correct answer (Sternberg & Wagner, 1993). In short, practical intelligence requires thinking "outside the box." Proponents of practical intelligence cite tacit knowledge as its central theme. This is the knowledge of managing people and tasks, and is measured through scenarios that require problem solving and decision making skills (Sternberg &Wagner, 1993).

Throughout history, the United States military has used general intelligence, more recently referred to as "cognitive ability," as an indicator for capacity in the realm of aviation (Pohlman & Fletcher, 1999). Cognitive abilities remain the most frequently studied predictors of pilot performance. The debate lies in whether or not this is an appropriate "yardstick." Critics of this method of selection argue there may not be a causal relationship between academic intelligence and job performance, and therefore between intelligence and performance in aviation, because it cannot adequately predict aircrew performance (Sternberg & Wagner, 1993; Hunter, 1989). It is conceivable, however, that specific cognitive abilities may be required to achieve unique job related tasks performed by pilots. Tests that examine psychomotor abilities are currently in the developmental phase and may prove to more accurately predict cockpit aptitude. Thus, the same critics that claim no correlation between intelligence and aviation performance concede that intelligence, in so far as it reflects aptitude for instrument and mechanical comprehension, is a valid predictor (Hunter, 1989). Past research connecting cognitive ability and flight school performance has shown conflicting results. Reinhart (1998) found academic performance and Primary Flight Training grades to be significantly related whereas Hilton and Dolgin (1991) concluded that intelligence and education were not linearly related to flight training success. Morales and Ree (1992) found, in a comparison study of cognitive ability and specific ability (job knowledge) that cognitive ability was a better predictor of five pilot criteria (including training performance and

actual flying performance) than was specific ability, in all five criteria (Carretta & Ree, 1994). One factor to consider in the debate over cognitive ability is that the sample in this study is considerably range restricted. It is not a representative sample of people or Americans in general, it is people who are college graduates, with a certain degree of motivation in the first place to be in the military and in an aviation program. It is difficult in this case to measure the difference in cognitive ability since the sample is expected to demonstrate very similar cognitive abilities.

3. Military vs. Academic Performance

Military performance is another potential predictor that is unique in that it has no defined equal in the civilian sector. It is an interesting subject for study, because it encompasses traits that are separate from academic performance yet have the potential to have a greater influence on overall performance. It is a behavioral trait that can best be described as a combination of discipline and motivation. Additionally, it can be seen as an intermediate predictor in that it can be partially attributed to cognitive ability and personality while it in turn predicts similar performance measures as cognitive ability and personality. This is evidence that each of the criteria at work here are not mutually exclusive and some correlation exists between them.

Military performance is the strongest predictor of aviation assignment at the U.S. Air Force Academy; however, critics argue that this imbalance of priorities is contributing to increased attrition in flight training (Weeks, 2000). As for the studies done on U.S. Naval Academy aviation assignment, the results are not as clear. Hafner (2000) in his study on Naval Flight Officer (NFO) performance concluded that Naval Academy graduates with higher military performance grades (Military Quality Point Rating, MQPR) were more likely to complete flight school training. Additionally, Hafner found academic grades (Academic Quality Point Rating, AQPR) not to be a significant predictor of completion. On the other hand, Reinhart (1998) found MQPR to be inconclusive in determining flight grades, but determined AQPR to be directly related to primary flight grades. Wahl, (1998) makes the most thought provoking conclusion when he deduces "a person's chances of graduating from primary flight training appear to depend not on one's academic prowess, race, or sex but on one's desire and motivation" (p. 59). Wahl makes this determination based on his calculations that the Pilot

Biographical Inventory, (a subtest of the Aviation Selection Test Battery, or ASTB) "is the most important criterion for predicting disqualification among Student Naval Aviators (student pilots) in primary flight training." (p. 59). Consideration should be given here that the population of people taking these tests are not a cross section of society, rather a group of people already selected for their exceptional academic performance. Because there is little variability in cognitive ability the range restriction may be a confounding factor.

4. Interviews

Several studies have determined that including a structured interview improved the validity of the pilot selection process. Typically these interviews are developed to focus on areas such as "educational background, motivation to fly, self-confidence and leadership, and flying job knowledge" (Carretta & Ree, 2000, p. 7). However, in one study, 223 US Air Force pilot trainees were subject to a structured interview in addition to taking the Air Force Officer Qualifying Test (AFOQT) and a computer based cognitive and personality test. When the interview scores were added to the regression equation containing the AFOQT and computer based test scores, no incremental validity was found. The interview did not account for any "unique" prediction of pilot performance (Carretta & Ree, 2000). Likewise, Hilton and Dolgin (1991) suggest that the interviews are often conducted improperly and are therefore not very useful.

B. AVIATION SELECTION TEST BATTERY

The Aviation Selection Test Battery (ASTB) is the examination administered by the U.S. Navy, Marine Corps and Cost Guard to prospective aviation training candidates. This test is the only aviation selection test in operation for the Naval Service; there are currently no tests that measure other aviation related characteristics such as psychomotor ability or information processing skills (Portman-Tiller et al, 1999). Approximately 10,000 applicants per year take the ASTB (Williams et. al, 1999).

The ASTB was first developed by the Naval Aerospace Medical Research Laboratory (NAMRL) during World War II and was revised in 1953 and 1971, with the current form updated in 1992 (Frank & Baisden, 1993, Portman-Tiller et al, 1999, Biggerstaff et. al, 1998). It can be administered in one of two forms, either paper-and-

pencil or computer based test (the Automated Pilot Examination, APEX). The test comprises five subtests: a Math Verbal Test (MVT) that evaluates math and reading comprehension, a Mechanical Comprehension Test (MCT), a Spatial Apperception Test (SAT) that asks the evaluee to determine the view seen from a cockpit based on several cockpit views and a picture of an aircraft at different flight attitudes, an Aviation and Nautical Information Test (ANI) that tests aviation and nautical history and terms, and finally, a Biographical Inventory (BI) that asks questions regarding personal history.

A six part composite score is derived from the five subtests. The six parts are the Academic Qualification Rating (AQR), Pilot Flight Aptitude Rating (PFAR), Naval Flight Officer Aptitude Rating (FOFAR), Pilot Biographical Inventory (PBI), Naval Flight Officer Biographical Inventory (FOBI), and the Officer Aptitude Rating (OAR). Currently, the minimums for qualification for Navy and Marine Corps officers are different. The Marine Corps requires scores of 4/6 (AQR/PFAR) and the Navy's minimums are 3/4 (AQR/PFAR) (Phillips, 2002a). Neither service has a minimum score for the OAR, and as of April 2002, the BI is no longer used for selection. The ASTB can be retaken if the desired scores are not achieved, however a retest invalidates the previous, and there is a minimum amount of time allowed between tests. The first retest is allowed after 30 days have passed, subsequent retests require 180 days between tests. Aviation hopefuls can retake the exam as many times as they are able to within these guidelines.

The most recent version of the ASTB was validated by the Educational Testing Service on applicants who had only taken the test once (Williams et. al, 1999). It is validated to predict performance in training through primary with the following breakdowns: the AQR is used to predict Aviation Preflight Indoctrination (API) grades, the PFAR is used to predict flight grades in primary, and the PBI was (prior to April 2002) used to predict attrition due to flight or academic failure or Drop-On-Request (DOR) at or before primary (Williams et. al, 1999, Portman-Tiller et al, 1999). The ASTB is a valid predictor of API, ground school and flight grades; but was not as good a predictor of attrition (Williams et. al, 1999). More recent research has concluded that that the AQR and PFAR do in fact accurately predict as advertised. Reinhart (1998) found that those who scored higher grades on the AQR and PFAR were more successful

in flight training than those with lower scores. In addition to being valid for predicting flight school performance, the ASTB has been found to be free of race and gender bias (Office of the Under Secretary of Defense Personnel and Readiness, 1999).

According to the Naval Operational Medicine Institute (NOMI), the organization responsible for overseeing the ASTB program, approximately 50% of aviation applicants are eliminated by not meeting the minimum standards of the ASTB (Portman-Tiller et al, 1999, Williams et. al, 1999). It is estimated that the use of the ASTB saves the Navy over $20 million each year (Arnold, 2002).

C. AIR FORCE SELECTION PROCESS

The United States Air Force uses slightly different methods than the Navy for selecting candidates for aviation training. The Pilot Candidate Selection Method (PCSM) is a tool that combines scores from the two selection tests used by the Air Force with a measure of flying experience to create a pilot aptitude composite (Carretta & Ree, 1994). The PCSM has been validated to predict probability of completing Undergraduate Pilot Training and number of flying hours needed to complete training (higher scores, greater probability) (Weeks, 2000). "The validity of the PCSM has been shown to come mostly from the measurement of cognitive ability, psychomotor ability, pilot job knowledge, and flying experience"(Carretta, 2000, p. 955).

As previously mentioned, the Air Force has two selection tests, the Air Force Officer Qualifying Test (AFOQT) and the Basic Attributes Test (BAT).

1. Air Force Officer Qualifying Test

In use since 1957, the AFOQT is used for officer commissioning and aircrew selection (Carretta, 2000; Carretta, 1997). It is a 16-test paper and pencil battery that is broken into 5 composites; Verbal, Quantitative, Academic Aptitude (verbal + quantitative), Pilot and Navigator-Technical (Carretta & Ree, 1996). The Pilot composite, similar to the ASTB, measures aviation and mechanical systems knowledge, spatial awareness and ability, and aeronautical concepts.

2. Basic Attributes Test

Implemented in 1993, the BAT is a computer based test used for selecting student pilots (Carretta, 1997). Its five tests measure cognitive ability, psychomotor

coordination, cognitive ability, and attitudes toward risk taking (Carretta, 1992; Carretta, 2000, Carretta, Zelenski, Ree, 2000).

There are minimum AFOQT score requirements for every pilot accession source except for the U.S. Air Force Academy (USAFA, the only source not required to take the AFOQT), but the minimums are different for each (Carretta, 2000; Weeks, 2000). Instead of using the AFOQT the USAFA uses a flight screening test (Weeks, 2000). Hunter and Burke (1994) base this decision on studies that show job sample tests to be the most valid predictors of flying training performance. Carretta and Ree on the other hand, found the AFOQT to be the "best predictor of pilot training attrition" (Weeks, 2000, p. 12).

Air Force Academy "service assignment." Candidate folders[9] go before a selection board where the committee members are to rank each individual on a 6-10 point scale; deciding for themselves the weighting of all information included (Weeks, 2000). The only guidance they are given is to use the "whole person concept" when making their determination (Weeks, 2000). Once all candidates are graded[10] they are put in rank order. There is no gender or race/ethnicity information provided to the board (Carretta, 2000).

A study was conducted using information from the selection boards from the classes of 1995, 1996, and 1997 to identify what variables were deemed the most important to the selection boards. The variable with the greatest weight was military performance, with an average impact of 4.78% ("a 10% increase in military performance average resulted in a 4.78% increase in average board rating") (Weeks, 2000, pg. 3). The other variable results were as follows: Academic average, 3.21%, flight screening performance, 1.4%, athletics .07%, and military commander (student leadership) position .04%. The study found that "officership," as measured by military performance, was found to be the most important factor for the selection boards. However, at this time USAFA (and Reserve Officer Training Corps, ROTC) graduates in flight training showed

[9] Candidate folders contain information on academic, military, and athletic performance data, evaluations, aviation and airmanship scores, extracurricular involvement, flight screening performance, conduct history and AFOQT scores, though not technically part of the selection criteria.

[10] If there exists more than a 1.5 point disparity between grades for an individual the case is discussed then re-graded.

lower "candidate ability levels" (Weeks, 2000, p. v) compared to trainees from the other accession sources (Officer Training School, Active Duty). The ultimate result of the study was that greater emphasis on "officership" rather than ability was leading to the decline in quality of students sent to flight training from the USAFA and ROTC. By disregarding the predictive quality of the AFOQT (USAFA does not use it at all, ROTC score requirements are lowest of any accession source) the USAFA and ROTC were contributing somewhat to unnecessarily high flight training attrition rates (Carretta, 2000). Ultimately, the study determined that, in order to minimize attrition, officership and ability should be equally weighted as selection factors (Weeks, 2000).

D. NAVY FLIGHT TRAINING PROCESS REVIEW

During the period of time covered in this paper, there were some major changes made to aviation training. Prior to the fall of 1997 the training pipelines were so backed up that it was taking on average 48 months to complete the jet pipeline, as opposed to the 30 months proposed in the syllabus (Gallardo et al., 2002). The student population had grown to 3,500, well above the 2,900 student ideal, and the population was increasing yearly. This backlog led to pools in training; long periods of idle time within stages of the program as well as between stages. Time-to-train was becoming such a problem that it gained the attention of the Chief of Naval Operations (CNO) in 1997. The Navy sought the help of a management consulting firm specializing in production process improvement. By early 1998 the assessment was complete and senior Navy and Marine Corps aviators were briefed on "principles of cycle time reduction, production process management, cultural change, and barrier removal" (Gallardo et al., 2002, p. 56). An instructor from one training squadron noted that after the process was reviewed and change recommendations were made, attrition had fallen from 20% to 15% because students were able to fly more regularly. At the end of Fiscal Year 2001 the student population in training had been reduced by more than 300 and the annual output had increased by over 200 students. This amounted to a 22% increase in aviator output, and time-to-train was decreased by an average of 30% (Gallardo et al., 2002). This drastic change to the training pipeline will most likely have an effect on performance if compared by year group.

E. ATTRITION

Though there are scores of reasons for attrition from aviation training (medical/physical deficiencies, academic trouble, not aeronautically adaptable) flight failure and Drop-On-Request (DOR) account for the vast majority, and are relatively equal in numbers. For the time period covered by this paper, attrition rates for DOR and flight failure for Naval Academy graduates were 36.5% and 37.2% of attrition respectively, or 4.8% and 4.9% overall. Similarly, according to the U.S. Air Force Air Education and Training Command "the most common reason for attrition is a failure to achieve basic flying proficiency" (Office of the Under Secretary of Defense Personnel and Readiness, 1999). Murray (1998) in a study spanning 1991 to 1995 found that commissioning source was significantly related to NFO attrition, and that the Naval Academy had the lowest attrition rates for performance and Drop-On-Request, though had the highest attrition rate for medical reasons. In the mid 1990s attrition across all military services was approximately 22% (Duke & Ree, 1996). Over the past 12 years the attrition rate for Navy and Marine Corps pilots has averaged close to 18% (Phillips, 2002b).

Only the training wing (TRAWING) commander or Naval Aviation Schools Command (NAVAVSCOLSCOM) Commanding Officer can terminate flight training. Occasionally students are afforded the opportunity for a pipeline or program[11] change after initial attrition. This is an option only if the recommendation for attrition was due to flight failure (not academic) or some physical reason (deteriorating eyesight, etc).

F. SUMMARY

"The best correlates of success in pilot training were job samples, gross dexterity, mechanical understanding, and reaction time. General ability, quantitative ability, and education were again found to be poor correlates of success" (Pohlman & Fletcher, 1999, p. 289). Clearly there are varying opinions as well as differing research results that attribute success in flight school to various criteria. One thing to consider is that each individual study looked at somewhat different criteria, and therefore was not comparing the same things as each of the others. Results may have been different had each study

[11] Pipeline change refers to a change from one pilot pipeline to another (i.e., jets to propellers) program change refers to a change from pilot to NFO, or vice versa.

looked at all of the same criteria. Another thing to consider when determining the relevance of this type of study is that all selection criteria look at success in training rather than in the "real world."

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III. RESEARCH DATA AND METHODOLOGY

A. PARTICIPANTS

This study uses a dataset from the U.S. Naval Academy Office of Institutional Research merged with a dataset from the Naval Operational Medicine Institute, Operational Psychology Department (NOMI) representing graduate/commissioned officer aviation selectees from the U.S. Naval Academy from the classes of 1995 – 1998. Because the target group is aviation selectees, it is not necessarily a representative sample based on gender, race and ethnicity. The purpose of this research is to make a determination regarding the effectiveness of the service assignment process at the U.S. Naval Academy. The population is based on those that service assigned aviation initially from the U.S. Naval Academy, rather than U.S. Naval Academy graduates that attended flight school (the latter being those that service assigned another warfare specialty then received a billet from an additional allocation prior to graduation, or service assigned another warfare specialty then did a lateral transfer into aviation later).

The classes of 1995 to 1998 were chosen because the bulk of the usable data from NOMI came from those classes. The files were merged using alpha code (a six digit identifying code) as the key variable. Prior to and after merging the files, cases were filtered and deleted (as described in the following text) to make a more manageable dataset.

1. Institutional Research Dataset

The Office of Institutional Research at USNA is responsible for maintaining the master file containing all information on each individual who has attended. It contains admissions information such as Scholastic Aptitude Test scores and Whole Person Multiple as well as student information including alpha code, academic grades, varsity athlete status, academic major and service assignment.

This dataset originally contained all USNA students from the classes of 1995 – 2005. The first step in paring down the dataset was to remove all that were not in the desired year groups. This was accomplished by using the CLASS YEAR variable and deleting all entries from the classes of 1999-2005. The next step was to eliminate all who

were not graduates/commissioned officers. To do this the ENROLLMENT STATUS variable was used, and all "currently enrolled" and "attrite" were removed, leaving only "graduate." The COMMISSIONING CODE variable was used, and all "Army," "Air Force," "Not Physically Qualified," and "Not Commissioned" were removed, leaving only "Navy" and "Marine Corps." Finally, the SERVICE ASSIGNMENT CODE variable was used to eliminate all that did not service assign "pilot." After this initial cleaning of the data, there were 1,114 USNA graduates from the classes of 1995-1998 who were commissioned into the Navy or Marine Corps and service assigned pilot.

2. NOMI Dataset

The dataset from NOMI was created based on a list of Social Security Numbers (SSN)[12] provided by Institutional Research in order to separate USNA graduates from the master NOMI file. Interestingly, because the Institutional Research database contains a file for all individuals who were ever enrolled at USNA since 1991[13], the list of SSNs contained graduates as well as nongraduates. When SSNs were compared against the master NOMI file, the resulting database contained 20 names of people who had at one time attended USNA but did not graduate, but eventually received a commission and a pilot billet. These cases were removed.

The NOMI dataset of 1,667 entries originally contained students from USNA classes of 1988 – 2000, though was not inclusive of all students from these year groups. It contained information such as ASTB scores (the standardized scores as well as raw score in each category, and scores on each test) grades in each phase of training, attrition vs. completion from aviation training, squadron names, and winging information.

As mentioned previously, the classes of 1995 to 1998 were chosen because the bulk of the usable data from NOMI came from those classes. The NOMI dataset was cleaned in a similar manner to the Institutional Research dataset using the CLASS YEAR and ENROLLMENT STATUS variables to obtain a file of USNA graduates from the classes of 1995-1998. Naval Flight Officers (NFOs) were left in the dataset at this point based on the knowledge that there could possibly be a few instances of individuals who

[12] Social Security Numbers were removed from database prior to distribution for privacy reasons.

[13] The class of 1995 would have enrolled in 1991.

service assigned pilot from USNA but subsequently became NFOs during flight training, either for medical reasons (deteriorating eyesight) or because they attrited out of a pilot program but were given the opportunity for a program change to NFO. This file contained 1,414 entries.

3. Merged Dataset

The merged dataset was created by using the Institutional Research dataset as the working data file and alpha code as the key variable with both files providing cases. This merge resulted in a file containing 1,538 cases. At this point, the dataset contained two variables that provided pilot vs. NFO information; the SERVICE ASSIGNMENT CODE variable from the Institutional Research dataset and the PROGRAM CODE variable from the NOMI dataset. The difference between these variables is SERVICE ASSIGNMENT CODE is simply what an individual service assigned on service assignment night, and PROGRAM CODE is the most recent program they were in during training. Therefore, there could be an individual with "pilot" in SERVICE ASSIGNMENT CODE and "NFO" in PROGRAM CODE, because they changed programs during training for one reason or another.

The discrepancy in the number of entries between the datasets can be accounted for in the following manner. NFOs were left in the NOMI dataset (for reasons explained previously); they accounted for 403 entries. Of the 1,538 entries in the merged file 388 were NFOs outright ("NFO" in SERVICE ASSIGNMENT CODE and PROGRAM CODE), 124 service assigned pilot but there was no matching NOMI information, and 36 did not service assign pilot at USNA but had a "pilot" PROGRAM CODE (received a late billet or lateral transfer). This left 990 entries that had information from both datasets; 975 who had "pilot" as both SERVICE ASSIGNMENT CODE and PROGRAM CODE, and 15 who had "pilot" as SERVICE ASSIGNMENT CODE, but "NFO" as PROGRAM CODE.

Table 1. Pilot vs. NFO breakdown in Merged Dataset

MERGED DATASET – 1,538 entries

USNA data	#	NOMI data
NFO	388	NFO
PILOT	124	NO INFO
??	36	PILOT
PILOT	975	PILOT
PILOT	15	NFO
	1,538	

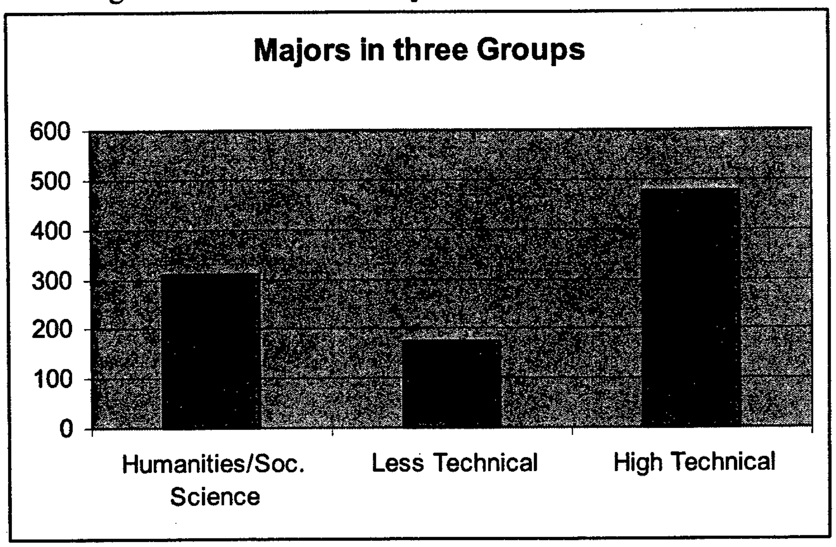
The 124 entries that lacked information in the NOMI database, the 388 that had service assigned NFO and the 36 that received pilot billets at a time other than service assignment were eliminated, leaving a dataset of 990. Because the attrition model was intended to predict who would attrite based on decision (Drop-On-Request) or poor performance, the 29 medically related attrites were also eliminated, resulting in an initial working database of 961 entries.

Finally, in order to get a more coherent picture of performance results, the files with grades that appeared unreliable for the particular test being run were eliminated. There were 14 files in the database that fell well outside of the reasonable range for raw API academic grade (NASCRAW) and 39 for raw Primary flight grade (PFG). Most of these cases turned out to be attrites, only a few had missing information completely. The final database for the regression on NASCRAW has 947 cases; 922 cases for PFG. The logistic regression on PRI_ATTR contains all 961 cases in the initial working database.

In the working database there are 829 Navy pilots and 132 USMC pilots. There are 26 African-Americans, 35 that are another race (Native American, Asian American, Other), and 78 that are female. The database is broken down roughly equally by graduating class, with 226 from the class of 1995, 260 from the class of 1996, 265 from the class of 1997, and 210 from the class of 1998. Academic major groups are represented as such: 477 from High Technical majors (all Engineering majors except for

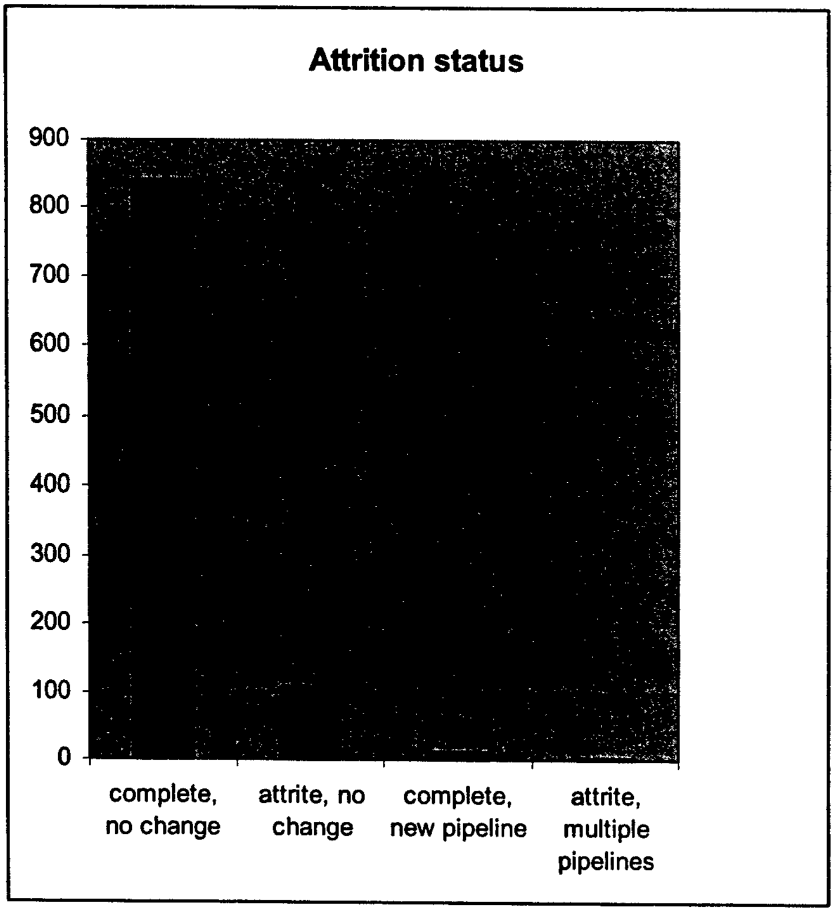
general; Physics, Chemistry, and Math) 176 from Less Technical majors (General Engineering, Science), and 308 from Humanities/Social Sciences (English, Economics, Political Science, History). Figure 1 shows a histogram for academic major distribution in the sample.

Figure 1. Academic Major distribution



Attrition information came from several variables. The CURRSTAT variable shows 109 attrites and 852 completes. To fully understand those figures the STATCODE variable must be observed. This variable has attrition broken into four categories: complete with no change (842), complete after program change due to attrition (10), attrite no change (107), and attrite in multiple pipelines (2). Figure 2 shows a histogram of the distribution of attrition by reason.

Figure 2. Attrition status code



With the medical attrites removed (29) there remain 119 people overall that attrited. According to the Primary Status (PRISTAT) variable, 78 of those occurred at or before the completion of Primary phase. The attrition data followed what was found in the literature review; that the vast majority of the attrition occurred as a result of Drop-On-Request (45.4%) and flight failure (46.2%)[14]. Overall attrition (discounting medical) was 12% with 66% of all attrition occurring during or before Primary phase. Figure 3 is a chart showing the breakdown of all attrition reasons throughout the entirety of flight school, while Figure 4 shows attrition only during or before Primary phase.

[14] Attrition percentages given are for the entirety of flight training. Percentages for attrition before or during Primary phase are 51.3% for DOR and 39.7% for flight failure.

Figure 3. Overall Attrition

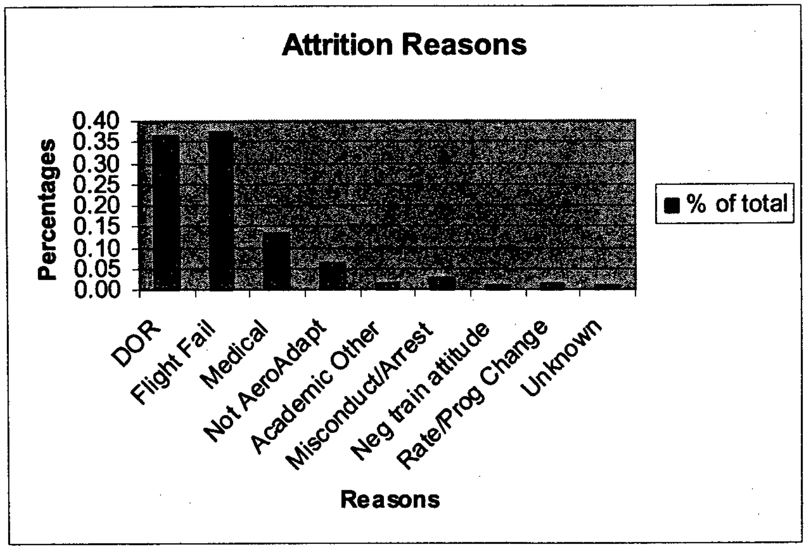
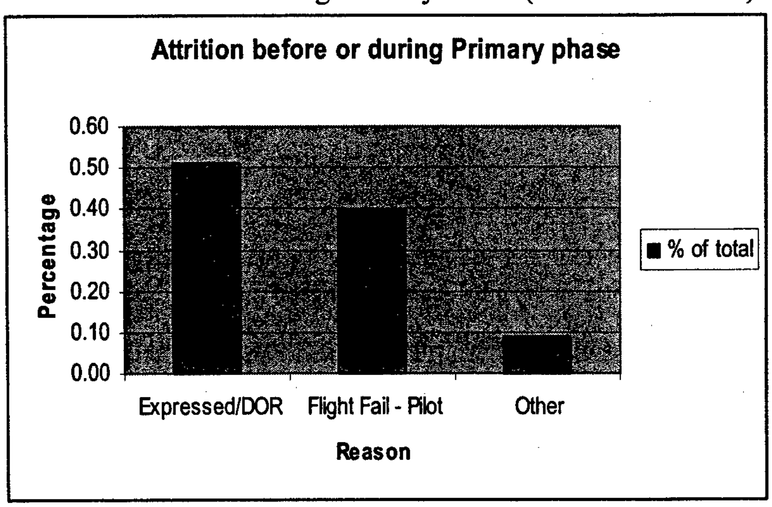


Figure 4. Attrition before or during Primary Phase (medical removed)



B. HYPOTHESES

The objective of this study is twofold; 1) to examine the current aviation assignment policy at the Naval Academy (predominantly based on ASTB and OOM) and determine if it is significantly related to pilot performance (academic, flying and attrition) in flight school, and 2) to examine alternative criteria to determine the possibility of developing a more effective model for predicting performance. Performance results from the first two stages of flight school will be used as the dependant variable; one for each of two linear regressions. These stages are the academic portion of Aviation Preflight Indoctrination (API) and the flying portion of Primary phase. Additionally, only those that attrited during or before the Primary phase will be considered attrites for the sake of the third test; a logistical regression.

C. REGRESSION ANALYSIS

To test the hypotheses, multiple regressions will be run on each dependant variable. First will be a linear regression to test for predictors of academic performance in API. The dependent variable will be raw API final grade (NASCRAW). Second will be a linear regression to test for predictors of flying performance in the Primary phase of training. The dependent variable for this regression will be raw Primary flight grade (PFG). Third and finally will be a logistic regression to test for predictors of attrition before or during the Primary phase of training, and the dependent variable for this test will be Primary attrite (PRI_ATTR).

1. Academic Performance in Aviation Preflight Indoctrination (API)

The Academic Qualification Rating (AQR) is the ASTB component that is designed to predict academic performance in API. AQR and OOM will be examined in the first set of analyses (test #1 through #3) to test the current method of aviation assignment. AQR is expected to be a positive and significant predictor of performance in API because it has been previously validated as such. OOM is expected to be negative[15] and significant because it is also a performance measure that is comprised nearly 65% of academics. The second set of analyses (test #4 through #7) will include additional variables to test whether or not they are better able to predict API performance than the

[15] OOM is expected to be negative because of the inverted scale, smaller numbers mean higher OOM.

method currently used. OOM will be broken into its two major components of CAQPR and CMQPR, and academic major information will be included. Previous studies have highlighted CMQPR and/or CAQPR as significant predictors of flight school performance in general. Because CAQPR is simply a measure of academic performance, it follows that it should be positively and highly associated with API final grades. CMQPR, though not a pure measure of academic performance, does have a small academic element by virtue of comprising nearly 11% of military courses and is expected also to be positively associated with API. Because of the technical nature of the courses in API, and further based on previous research, it is expected that individuals in the High Technical (HITCH) major category will perform better in API than Less Technical (LESSTCH) and Humanities/Social Sciences (HUMSS).

Lastly, each majors group will be combined with CAQPR to create grades-within-major interaction variables. Creating these variables will allow analysis of an individual major to see if there is a significant difference in API grades between individuals with different CAQPRs within the same major. In other words, this will show if better performance within a major results in better performance in API as compared to better performance in general as shown by the CAQPR alone. Just as a better CAQPR is expected to result in better API grades, better grades within a major are likewise expected to present the same result, though it is unclear if the results will be the same for the different majors (ie, the difference in API grades for a 2.0 CAQPR and a 3.0 CAQPR for a HITCH major, as compared to the difference between a 2.0 CAQPR and 3.0 CAQPR for a HUMSS major).

Class years are included in each test and demographics are included in the second and subsequent tests as controls. Previous research has differed on whether or not females and minorities perform at a lower level than majority males in flight school. Therefore, these demographics are included as co-variates so as to avoid confounds with the independent variables of primary interest.

2. Flying Performance in Primary Phase

Predicting flying performance, especially from the criteria available, is somewhat more complicated than predicting academic performance. As was quoted in the literature

review, "The best correlates of success in pilot training were job samples, gross dexterity, mechanical understanding, and reaction time. General ability, quantitative ability, and education were again found to be poor correlates of success" (Pohlman & Fletcher, 1999, p. 289). Unfortunately, job samples, gross dexterity, and reaction time are not available to be measured or quantified, and mechanical understanding is limited to what can be measured in the ASTB. Quantitative ability and education are available, poor correlates though they may be.

The Pilot Flight Aptitude Rating (PFAR) is the ASTB component validated to predict flying performance in the Primary phase. PFAR and OOM will be examined in the first set of analyses (test #1 through #3) to test the current method of aviation assignment at the Naval Academy. PFAR is expected to be a positive and significant predictor of flying performance because it has been previously validated as such and OOM is expected to be negative and significant because it is also a performance measure, though admittedly unrelated to flying. For this reason, OOM is not expected to be as strongly associated as in the regression on API grades.

The second set of analyses (test #4 through #6) will include additional variables to test whether or not they are better able to predict flying performance than the current factors (PFAR and OOM) used to screen aviation applicants. Just as in the first regression, OOM will be broken into its two major components of CAQPR and CMQPR, and academic major information will be included. As the literature review shows, there are previous studies that disagree on whether or not CAQPR and CMQPR are related to flying performance. CAQPR is expected to be positively though weakly associated simply because it is a performance measure, not necessarily because it is a measure of academic performance. CMQPR is expected to be positively and weakly associated as well, because military performance is perhaps the closest thing to a motivation measure that is available. Academic majors are not expected to be associated with flying performance based on previous research that has found academic majors unrelated to Primary flight grades. Because of this expectation and the expectation that CAQPR will be only weakly associated, grades in majors are not expected to be associated with flying performance.

Just as in the first set of regressions, class years are included in each test and demographics are included in the second and subsequent tests as controls. Again, it is expected that there will be no significant difference in the performance of females and minorities from majority males.

3. Attrition During or Before Primary Phase

Wahl (1998) made the assertion that "desire and motivation" (p. 59) were more indicative of completion of Primary training than were cognitive ability, gender or ethnicity. That would certainly be true for the 51.3% who chose to DOR during or before the completion of Primary, and to a lesser degree those that attrited as a result of flight failure. The attrition model will be similar to the previous two in that it will examine the ASTB component (Pilot Biographical Inventory, PBI) and OOM first, and then in subsequent tests include the alternative variables. PBI was previously validated to predict attrition during or before the Primary phase, but has recently been removed as a requirement for achieving an aviation billet, due to its lack of predictive power. It is being included here to see if this test finds it insignificant as well, as is expected. OOM is expected to be negative and weakly associated because it can be argued that someone who worked hard enough to graduate with a high OOM must have been motivated and would therefore also be motivated to complete flight school.

In the second set of analyses, the same alternative variables will again be used. Again, CMQPR is as near a motivation measure as is available, but is only expected to be weakly associated. Based on the literature review CAQPR is not expected to be a significant predictor of completion, neither is academic major selection, and based on these expectations, neither is grades in major. Additionally, gender and race/ethnicity are included as controls.

D. MEASURES/PROCEDURES

To test the hypotheses, multiple regressions will be run on each dependant variable. The results from each set (one set for each dependant variable) of regressions will be documented in a table and will be divided into two sections, the first showing the results for the current method of assigning aviation billets, the second showing the results for the alternative variables. First will be a linear regression to test for predictors of

academic performance in API. The dependant variable will be raw API final grade (NASCRAW). Second will be a linear regression to test for predictors of flying performance in the Primary phase of training. The dependant variable for this regression will be raw Primary flight grade (PFG).

Third and finally will be a logistic regression to identify predictors of attrition before or during the Primary phase of training. The dependant variable for this test will be Primary attrite (PRI_ATTR). Because this test involves a dichotomous variable as the dependant variable, the linear model from the first two tests cannot be used. Rather, a "more complex non-linear" (Bowman, 1998, pg. 1) model will be used. After the regression results are obtained, "marginal effects" will be calculated to determine the probability of attrition for a unit change in each independent variable.[16]

Table 2 shows a generalized example of what the results tables will look like, and the variables that will be used in each section.

[16] See Bowman, 1998 page 1 for a further explanation on marginal effects.

Table 2. Regression Results (example)

Predictor Variables	Current Selection Method tests for Analysis One	Alternate Variables tests for Analysis Two
DEMOGRAPHICS		
Female	X	X
African American	X	X
other race (a)	X	X
class of 1996	X	X
class of 1997	X	X
class of 1998	X	X
ASTB		
academic qualification ratio	X	X
pilot flight aptitude rating	X	X
pilot biographical inventory	X	X
Order of Merit	X	
GRADES		
Academic grades		X
Military Grades		X
ACADEMIC MAJOR		
Humanities/Social Sci major		X
Less Tech major		X
Humanities/Social Sci grades		X
Less Tech grades		X

a. Other non-Caucasian race besides African American.

b. ** indicates statistically significant at p≤.01.

c. * indicates statistically significant at p≤.05.

SUMMARY STATISTICS:		
F	X	X
Adjusted R^2	X	X
Cases	X	X

1. Dependent Variables

NASCRAW – Raw final academic grade for API. This continuous variable is on a 0-100 point scale with a mean of 92.9 and standard deviation of 3.62. A grade of 80 is the minimum required to pass, therefore all grades below 80 were eliminated. NASCRAW will be the dependent variable used in the linear regression on API grades. Figure 5 is a histogram showing the distribution of the NASCRAW grades from the

sample. Due to the truncated scale the observed variation in scores is small. For this reason, in the data analysis chapter all results will be discussed in terms of percentile changes.

PFG – Raw final flight grade from Primary phase. This continuous variable is on a 0-4.0 scale with a mean of 3.03 and a standard deviation of .11. PFG will be the dependent variable used in the linear regression on Primary flight grades. Figure 6 is a histogram showing the distribution of PFG from the sample. Similar to NASCRAW, PFG is also on a small scale with little observed variation in grades. Again, results will be given in terms of percentile changes.

PRI_ATTR – Attrite before or during Primary phase. PRI_ATTR will be the dependent variable for the logistical regression on attrition. The PRISTAT variable was recoded into this dichotomous variable. 8.1% of the sample attrited before or during Primary.

Figure 5. Raw API grade distribution

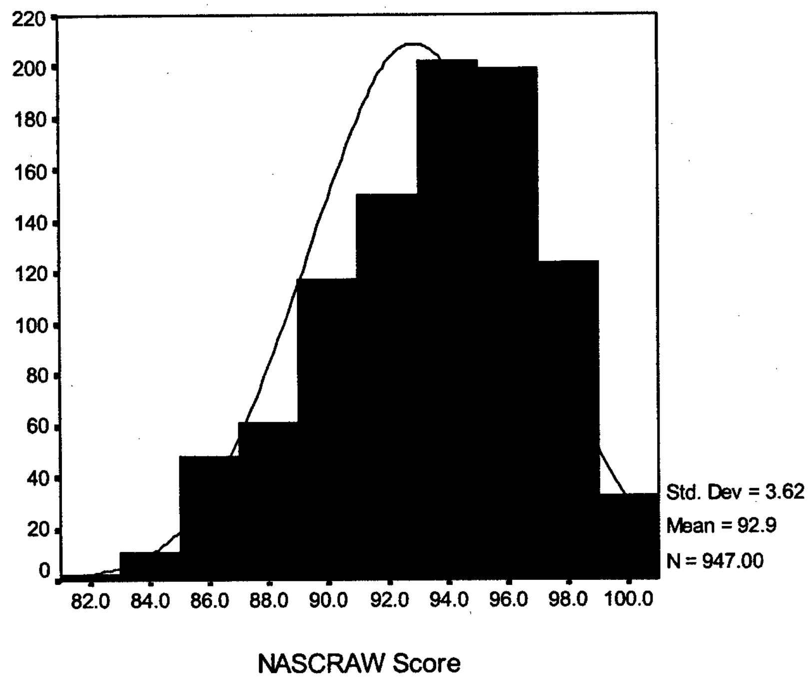
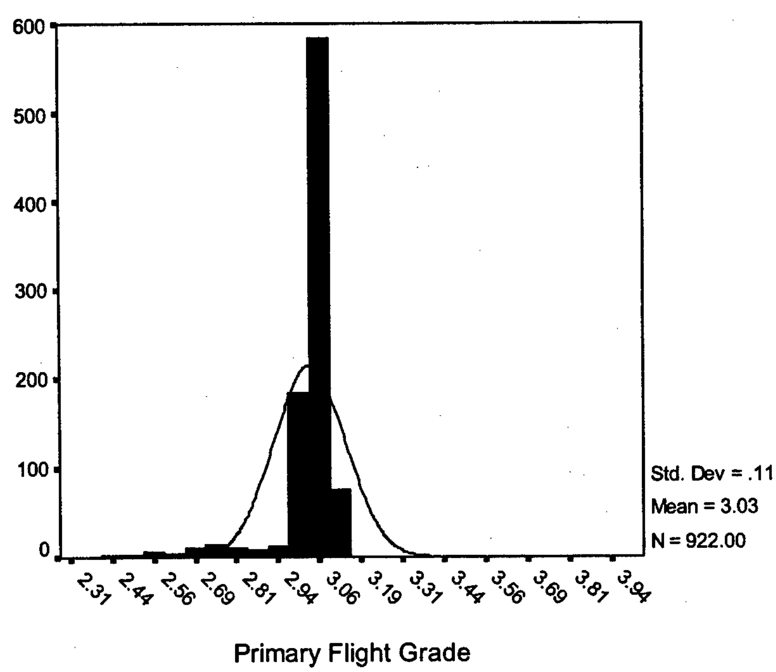


Figure 6. Primary flight grade distribution



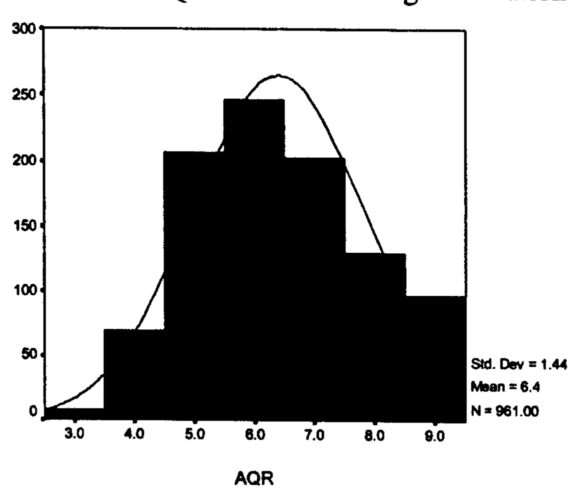
2. Independent Variables

ASTB components and OOM will be the Independent Variables for the first set of analyses in each regression to determine efficacy of the current aviation assignment method at the Naval Academy. The second set of analyses will still contain the appropriate ASTB component for the given test, as well as the alternate variables. Criteria that are measured at USNA will serve as most of the Independent Variables, with demographic and graduation year information used as controls. With the exception of the predictive ASTB component in each regression, the same Independent Variables will be used for each of the three models.

a. ASTB Variables

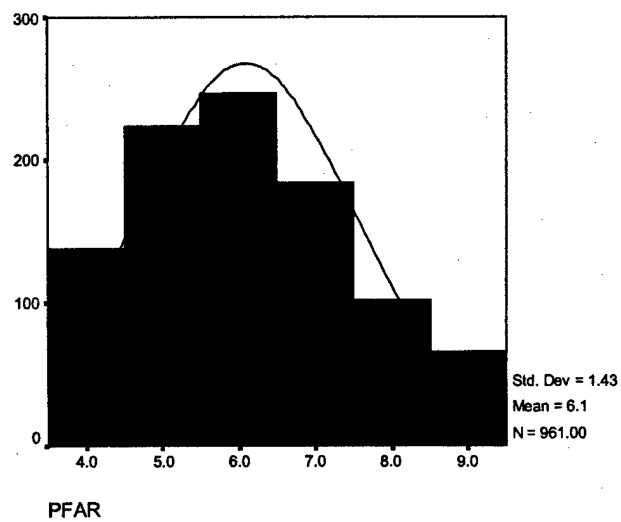
AQR – Academic Qualification Rating. This is one element of the six part composite score generated from ASTB results. It has been validated to be predictive of academic grades in API. This continuous variable is on a 3-9 point scale (because a score of 3 is the minimum for qualification) with a mean of 6.40 and a standard deviation of 1.44. Figure 7 is a histogram showing AQR distribution in the sample. AQR will be used in the linear regression on API grades. Though a specialized test result, because AQR is ultimately a measure of academics, it is expected to be highly correlated with OOM and CAQPR. If so, its predictive power should be significantly decreased when these variables are added to the model. Because it has been previously validated to predict API grades, it is expected to be positive and significant.

Figure 7. Academic Qualification Rating distribution



PFAR – Pilot Flight Aptitude Rating. This is one element of the six part composite score generated from ASTB results and has been validated to be predictive of flying grades in Primary. This continuous variable is on a 4-9 point scale (because 4 is the minimum required score required for qualification) with a mean of 6.09 and a standard deviation of 1.43. Figure 8 is a histogram showing PFAR distribution in the sample. PFAR will be used in the linear regression on Primary flight grades. PFAR is a unique criteria measure in that it tests flight aptitude and is therefore completely unrelated to any of the other variables. Because it has been previously validated to predict Primary flight grades, PFAR is expected to be positive and significant.

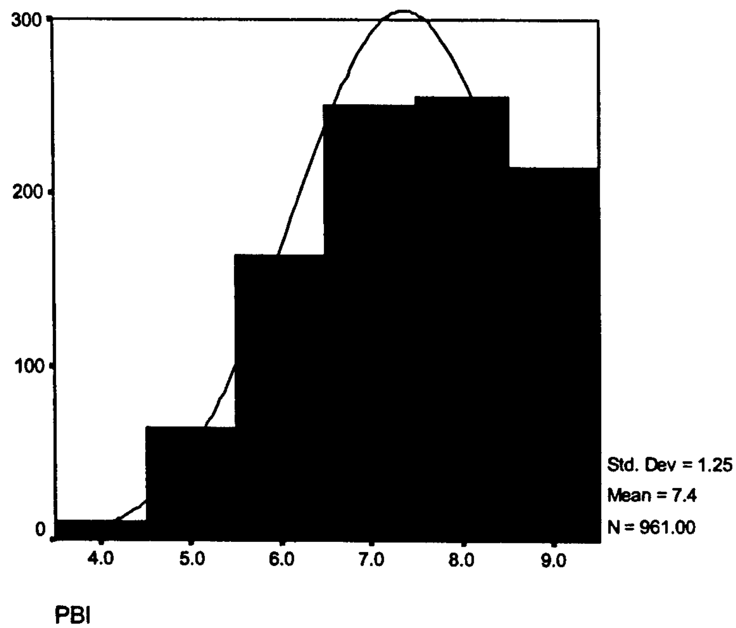
Figure 8. Pilot Flight Aptitude Rating distribution



PBI – Pilot Biographical Inventory. This is one element of the six part composite score generated from ASTB results. It has been validated to predict attrition, and found statistically significant to do so in previous research, but in April 2002 it was determined no longer to be an effective predictor of attrition and the minimum score requirement was eliminated. This numerical variable is on a 0-9 point scale with a mean of 7.37 and a standard deviation of 1.25. Figure 9 is a histogram showing PBI distribution in the sample. PBI will be used in the logistic regression on attrition during or before Primary. Perhaps the nearest thing to PBI that is collected at the Naval Academy is the Myers-Briggs or the Strong Interest Inventory personality tests. These tests, however, are not used in aviation assignment and are not included in this research.

Because it is no longer used as part of the selection criteria, PBI is expected to be positive though not significant.

Figure 9. Pilot Biographical Inventory distribution



b. Order of Merit

OOM – Order of Merit, similar to class rank. Order of Merit is a continuous, ordinal variable. As described earlier, OOM comprises academic and military classes (64.48%), military performance (17.68%), conduct (7.8%), physical education (6.66%) and athletic performance (3.38%). OOM is currently the predominant criteria in aviation assignment at the Naval Academy making up 65% of the Service Assignment Multiple for aviators. OOM is expected to be negatively associated with all three dependant variables.

c. Demographic Variables

The demographic variables are added to the models as controls and, with the exception of gender, are therefore not discussed in as great of detail as the other variables.

FEMALE – This discrete variable was recoded as a dummy variable of the SEX variable. As stated before, there were 78 (8.1%) females in the sample. MALE is the omitted reference variable. Previous research from the early 1990s found that

females scored significantly higher on the Aviation Qualification Test but then performed at a significantly lower level in API. More recent tests found no significant difference in gender performance in completing flight training or flight school grades. There is expected to be no significant difference in gender in academic or flying performance or attrition.

AFRAMER – This discrete variable is a dummy variable of the RACECAT (Race Category) variable. The RACE variable was recoded into RACECAT, ["C" (Caucasian) = 0 (WHITE), "N" (African American) = 1 (BLACK), "M" (Asian American), "R" (Native American), or "X" (other) = 2 (OTHER)]. If "1 (BLACK)" then "selected." There are 26 (2.7%) African Americans in the sample.

OTHRACE – This discrete variable is a dummy variable of the RACECAT (Race Category) variable. If "2 (OTHER)" in the RACECAT variable, then "selected." There were 35 (3.6%) that classify as other race (Asian American, Native American, Other) in the sample.

CAUCASIAN – This is the omitted reference variable. There are 900 in the sample.

YEAR95, YEAR96, YEAR97, YEAR98 – The class year categories are dummy variables of the GRAD_YR variable. YEAR95 is the omitted reference variable.

d. Grades

CAQPR and CMQPR are the two predominant variables that comprise OOM. Previous research disagrees on whether or not these individual components significantly predict performance in flight school or completion.

CAQPR – Cumulative Academic Quality Point Ratio, similar to grade point average on all academic classes. CAQPR is a continuous variable with a realistic range of 2.0 to 4.0 (a minimum of 2.0 is required to graduate). CAQPR is expected to be positively and strongly associated with API grades, positively but weakly associated with flying grades, and unrelated to attrition.

CMQPR – Cumulative Military Quality Point Ratio. CMQPR comprises military performance (44.56%), conduct (19.66%), physical education (16.78%), military

courses (10.48%), and athletic performance (8.52%). CAQPR is a continuous variable with a realistic range of 2.0 to 4.0 (a minimum of 2.0 is required to graduate). CMQPR is expected to be positively associated with API and flying grades, and completion.

e. Academic Majors Variables

Previous research has found academic major to be a valid predictor of flight school academic performance as well as completion. In most studies engineers have performed at a significantly higher rate and are more likely to complete than are non-technical majors. On the other hand, however, there are studies that show majors to have no significance in predicting completion. Figure 9 shows the distribution of academic majors in the sample.

HUMSS – Humanities/Social Sciences Major. The MAJOR_C (Major Code) variable was recoded to reflect three grouped majors' variables. The dichotomous HUMSS variable includes Political Science, English, Economics and History majors. There are 308 (32%) individuals with a HUMSS major in the sample. HUMSS is expected to be negatively related to API grades due to the technical emphasis of the courses, however it is expected to be unrelated to flying performance or attrition.

LESSTCH – Less Technical Major. The MAJOR_C (Major Code) variable was recoded to reflect three grouped majors' variables. The dichotomous LESSTCH variable includes General Engineering, Computer Science, General Science and Oceanography majors. There are 176 (18.3%) individuals with a LESSTCH major in the dataset. Because the LESSTCH variable is the "middle of the road" between HUMSS and HITCH majors, it is not expected to be significantly related to performance or attrition.

HITCH – High Technical Major. The MAJOR_C (Major Code) variable was recoded to reflect three grouped majors' variables. The dichotomous HITCH variable includes all Engineering (except for General Engineering), Math, Chemistry, and Physics majors. There are 476 (49.6%) individuals with a HITCH major in the dataset. HITCH serves as the omitted reference variable. HITCH majors are expected to be positively and significantly related to performance in API, but not in flying or attrition because these are more abstract factors not as easily explained by course of study.

Lastly, the grades-within-major interaction variables will allow analysis of an individual major to see if there is a significant difference in performance and attrition between individuals with different CAQPRs within the same major. This will show if better performance within a major results in better performance in flight school and less likelihood for attrition as compared to better performance in general as shown by the CAQPR alone. It is expected that the result will be zero for all tests, indicating that a better grade within a major will have the same effect for all majors.

HMSSQPR – This computed variable comprises HUMSS and CAQPR variables multiplied together. Therefore its value is either a CAQPR (if the individual was a HUMSS major) or zero if not. It is a numerical variable with a realistic range of 2.0 to 4.0.

LSTCHQPR – This computed variable comprises LESSTCH and CAQPR variables multiplied together. Therefore its value is either a CAQPR (if the individual was a LESSTECH major) or zero if not. It is a numerical variable with a realistic range of 2.0 to 4.0.

HITCHQPR – This computed variable comprises HITCH and CAQPR variables multiplied together. Therefore its value is either a CAQPR (if the individual was a HITCH major) or zero if not. It is a numerical variable with a realistic range of 2.0 to 4.0. This is the omitted reference variable.

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IV. DATA RESULTS AND ANALYSIS

A. INTRODUCTION

The purpose of this study is to determine which characteristics and outcomes that are measured/determined at the Naval Academy serve as the best predictors of attrition from naval pilot training before or during the Primary phase, as well as performance in the first two stages of training: the academic portion of Aviation Preflight Indoctrination (API) and the flying portion of Primary phase. The reason for this is twofold; 1) to examine the current aviation assignment policy at the Naval Academy (predominantly based on ASTB and OOM) to determine if it is significantly related to pilot performance (academic, flying and attrition) in flight school, and 2) to examine alternative criteria to determine the possibility of developing a more effective model for predicting performance.

To test the major hypotheses discussed in the previous chapter, three separate regressions are run. The first is a linear regression to test for predictors of academic performance in API. The dependent variable is the raw API grade (NASCRAW). The second is a linear regression to test for predictors of flying performance in the Primary phase of training. The dependent variable for this regression is raw Primary flight grade (PFG). The third and final test is a logistic regression to test for predictors of attrition before or during the Primary phase of training, and the dependent variable for this test is attrition during or before Primary phase (PRI_ATTR).

As shown by the adjusted R^2, the addition of variables in each subsequent test improves the fit of the model to the dependent variable[17]. While many of the independent variables are found to be statistically significant, the overall fit leaves much unexplained variance. As mentioned in chapter one, ASTB and OOM comprise the majority of the aviation service assignment multiple at the Naval Academy, at 25% and 65% respectively. For this reason these variables are the primary focus of the regression models and will be discussed together as analysis one. Since the one universal criterion

[17] Though it appears as if the adj R^2 decreases from test #4 to test #5, tests #5 and #6 are actually similar tests to #3 and #4 but OOM has been replaced by CAQPR and CMQPR.

used by all accession sources for determining aviation training eligibility is the ASTB, in each of the regressions the applicable ASTB component alone (with dummy variable graduation years to capture possible year group differences used as a constant) comprises the first test. Demographic variables are added in the second test, and finally OOM is added in the third and final test of the first group of analyses (i.e., Analysis One). A second subset of analyses (i.e., Analysis Two) comprises the remaining tests in the model and will examine if additional data related to USNA can add significant value to predicted classroom performance in API, flying performance in Primary phase, and attrition from training.

B. LINEAR REGRESSIONS ON API GRADES

Seven regressions are run in the test. Each regression introduces new variables to show the change in the initial estimate of ASTB and OOM on API grades as well as to improve the specification of the overall model. Graduation year is included in each test as a control (and demographics in each test after the first), and in subsequent tests the predictor variables of Order of Merit, Academic and Military grades and major are sequentially added and compared. There are several categorical variables added that have an omitted reference value (e.g. "1995" for graduation years, "male" for gender, etc). In other words, the interpretation of the results of the regression for these variables are made in reference to the omitted value. What follows is a breakdown of the regression results as well as an analysis to explain reasons behind the major results. Table 1 contains regression outcomes for seven regressions run on the selected prediction variables for API grades. The unstandardized coefficient is given as well as whether or not the result is statistically significant which is annotated by an asterisk.* The full regression results are also displayed in Appendix A. There are 947 cases in this model after all cases with a NASCRAW of less than 80 are removed.

Table 3. Regression results on raw API final grade

	Analysis One			Analysis Two			
	Current	Selection	Method	Alternate Variables			
Predictor Variables	**test #1**	**test #2**	**test #3**	**test #4**	**test #5**	**test #6**	**test #7**
DEMOGRAPHICS							
Female		-.801/*(c)	-1.115/**	-1.21/**	-1.156/**	-1.259/**	-1.270/**
African American		-0.603	0.518	0.549	0.607	0.656	0.731
other race (a)		-0.809	-0.354	-0.35	-0.371	-0.377	-0.358
class of 1996	-1.174/**	-1.171/**	-.994/**	-1.056/**	-.970/**	-1.086/**	-1.074/**
class of 1997	-1.485/**	-1.498/**	-1.161/**	-1.152/**	-1.206/**	-1.263/**	-1.297/**
class of 1998	-1.065/**	-1.022/**	-.687/*	-.765/**	-.661/*	-.822/**	-.890/**
ASTB							
academic qualification ratio	.928/**(b)	.881/**	.624/**	.496/**	.558/**	.423/**	.425/**
Order of Merit			-.006/**	-.006/**			
GRADES							
Academic grades					3.540/**	3.587/**	3.171/**
Military Grades					1.047/*	0.614	0.514
ACADEMIC MAJOR							
Humanities/Social Sci major				-1.31/**		-1.354/**	-4.912/**
Low Tech major				-0.49		-0.479	-2.118
Humanities/Social Sci grades							1.215/*
Low Tech grades							0.546

a. Other non-Caucasian race besides African American.
b. ** indicates statistically significant at p≤.01.
c. * indicates statistically significant at p≤.05.

SUMMARY STATISTICS:							
F	45.0/**	27.0/**	57.9/**	51.0/**	56.7/**	51.2/**	43.9/**
Adjusted R^2	0.157	0.161	0.325	0.346	0.346	0.369	0.371
cases	947	947	947	947	947	947	947

1. Analysis One - Aviation Qualification Ratio (AQR) and Order of Merit (OOM)

It was discussed previously that the Aviation Qualification Ratio (AQR) is the component of the ASTB that has been validated to predict academic performance in API. AQR, along with dummy variable graduation years, is the only variable run in the first model specification (test #1) to get an idea of its predictive ability alone. The estimated impact of AQR is statistically significant and suggests that a one point increase in AQR results in a .928 improvement in NASCRAW. This further results in an 11 percentile point change (51st percentile to 62nd). In subsequent tests, as additional variables are added, the value of the AQR unstandardized coefficient remains significant but the value is reduced. When demographic variables are added in test #2 the value of AQR is reduced, though only slightly (from .928 to .881). However, it is reduced to nearly two thirds its original value (.624) when OOM is added to the regression in test #3, suggesting AQR and OOM are significantly related (i.e. They are each academic measures).

Order of Merit is shown to be negative and significant. This sign follows since a lower number for Order of Merit actually equates to a higher place in class rank. A 100 place improvement in OOM results in a .6 point increase in NASCRAW or a 1 percentile point change (from the 51st to the 52$^{nd)}$. This result leads one to believe that, while positive and significant, OOM does not contribute much to the model since its impact on NASCRAW is so small.

From the Adjusted R^2 it is known that the variables in analysis one, or the current method used for aviation assignment at the Naval Academy, account for approximately one third of the variation in the model (.325). While both of these variables are positive and significant and support the current method of assigning aviation billets, analysis two will attempt to increase the variance by adding other variables to the model.

2. Analysis Two – Alternate Variables

AQR is further reduced to almost half (.496) when academic major information is added in test #4, however OOM stays the same. The notable reductions in the value of

AQR is influenced by adding variables to the model that are highly correlated with AQR and help to further predict the performance outcome. Academic major selection appears to have an impact on the AQR value, but not on the OOM (remains at .006). Tests #5 and #6 are similar to #3 and #4 in that OOM is replaced by its component variables, CAQPR and CMQPR. The results from these two sets of tests are similar, however the AQR value is reduced further (.496 in test #4 to .423 in test #6) and adjusted R^2 is larger (.346 in test #4 to .369 in test #6) in tests #5 and #6 indicating that these predictors are stronger.

Neither race variable (African American, Other Race) is statistically significant in any of the tests in which they are included, however in test #2 the model predicts that holding other variables constant, females tend to score .801 points lower in API. This result is statistically significant. Interestingly, as additional variables are added, the female coefficient is increased rather than reduced in contrast to the AQR coefficient. In the final test (test #7) with all of the variables included, all other things being equal, being female resulted in a 1.27 points lower NASCRAW score. On average, men would score at the 50th percentile while women possessing all of the same traits would score at only the 32nd. This result contradicts the more recent findings from the literature review (Reinhart, 1998; Hafner, 2000) though is at least somewhat aligned with the Baisden study from 1992. The difference being, in her study females performed significantly worse in API after scoring higher on the AQT, and in this sample the females actually scored significantly lower on the AQR as well (5.44 compared to 6.48 for the males). For some unexplained reason females selecting aviation during the period of time covered in this thesis, while successful overall, recorded lower grades than the males.

Military and Academic grades are added in test #5. Military grades are positive and significant (1.047) when grades are run separately, but no longer significant when academic major information is added in test #6. This result was not expected since CMPQR has (though small, 11%) an academic component to it. However, the literature gave no indication that military performance would be related to API grades (only flying grades and completion).

The estimated impact of academic grades on API grades is positive and significant. It follows that academic grades should be predictive of API performance since the dependant variable is also an academic measure. The assumption is that high performance in one academic arena, especially one as difficult as the Naval Academy, should ideally predict high performance in another academic arena. By looking at the adjusted R^2, it appears that replacing OOM with academic and military grades improves the overall fit of the model (.325 to .346). One possible explanation for this is, while CAPQR and CMQPR comprise the majority of OOM (approximately 83%) there are parts of OOM that likely have nothing at all to do with API performance (conduct, PE, athletics) and could actually detract from the model in this case. Test #5 shows that a one point increase in CAQPR results in a 3.54 point increase in one's NASCRAW score or a 22 percentile points difference (51st to 83rd).

Less Technical majors and Humanities/Social Science majors are predicted to do less well than High Technical majors, though only the Humanities/Social Science results are statistically significant. On average, a HUMSS major NASCRAW score is predicted to be anywhere between 1.31 and 1.35 points lower than a High Technical major[18]. All other variables held constant, a HITCH major would perform at the 51st percentile while the HUMSS major was at the 32nd percentile. It appears that the types of classes included in the API curriculum are better suited to individuals with HITCH majors. This makes sense given such classes as engineering and aerodynamics. The interesting question to raise here is, is the performance of a HITCH major higher because of the previous exposure to the more technical environment, or is it attributable to the quality of person who selects into a HITCH major in the first place?

Including the grades-in-major interaction variables in test #7 presents an interesting outcome. CAQPR is still statistically significant for everyone; however it has a much larger impact for HUMSS majors. Essentially, a one point increase in CAQPR results in a 3.17 points increase in NASCRAW for everyone, but for a HUMSS major a one point increase in CAQPR results in an additional increase in NASCRAW of 1.22, or a 4.39 points increase. Improving CAQPR by one point results in an increase of 32

[18] 1.35 when using CAQPR and CMQPR in the regression, 1.31 when using OOM.

percentile points (ie. From the 51st to the 83rd) for grades on average and an increase of 40 percentile points (ie. 51st to 91st) for HUMSS majors' grades.

AQR is clearly a strong predictor of API performance, but alone only accounts for 16% of the variance in the model. In order to improve the over all fit one of two things can be done; add OOM (increases adjusted R^2 from .157 to .325) or all of the other variables (adjusted R^2 is increased to .371). After including all variables in the final test of analysis two, it is clear that, at least in regards to API grades, these alternate variables are stronger predictors of performance in API. The adjusted R^2 of Test #7 (.371) is a 14% improvement in explaining the variation in the model over that of Test #3 (.325) at the end of Analysis One.

C. LINEAR REGRESSIONS ON PRIMARY FLIGHT GRADES (PFG)

Table #2 contains results for six[19] regressions run on the selected prediction variables for Primary phase flight grades in the same format as Table #1. There are 922 cases in this model after all PFGs of "0" are removed. As in the previous section, the ASTB component (PFAR) and OOM will be reviewed as Analysis One, with the other variables examined in Analysis Two. The full regression results are also displayed in Appendix B.

19 Because the interaction variables were not significant in this model, test #7 was eliminated.

Table 4. Regression Results on Primary Phase Flight grade

	Analysis One			**Analysis Two**		
	Current Selection Method			**Alternate Variables**		
Predictor Variables	**test #1**	**test #2**	**test #3**	**test #4**	**test #5**	**test #6**
DEMOGRAPHICS						
Female		0.015	0.014	0.014	0.014	0.013
African American		-0.018	-0.007	-0.007	-0.004	-0.004
other race (a)		-0.043/**	-0.040/**	-.039/**	-.039/**	-.039/**
class of 1996	-0.023/*(c)	-0.025/**	-0.023/*	-.024/*	-.022/*	-.022/*
class of 1997	-.044/**	-.046/**	-.044/**	-.044/**	-.042/**	-.042/**
class of 1998	-.091/**	-.093/**	-.091/**	-.091/**	-.088/**	-.088/**
ASTB						
Pilot Flight Apt Rating	.006/**(b)	.007/**	.005/*	.005/*	.005/*	.005/*
Order of Merit			-.00005/**	-.00005/**		
GRADES						
Academic grades					.029/**	.029/**
Military Grades					0.02	0.02
ACADEMIC MAJOR						
Humanities/Social Sci major				-0.004		-0.003
Low Tech major				-0.002		0.0007

a. Other non-Caucasian race besides African American.
b. ** indicates statistically significant at $p \leq .01$.
c. * indicates statistically significant at $p \leq .05$.

SUMMARY STATISTICS:						
F	24.7/**	16.3/**	15.9/**	12.7/**	15.2/**	12.4/**
Adjusted R^2	0.093	0.104	0.115	0.113	0.122	0.12
Cases	922	922	922	922	922	922

1. Analysis One – Pilot Flight Aptitude Rating (PFAR) and OOM

This component of the ASTB has been previously validated to predict performance in Primary flight grades and is proven statistically significant in this model as well. PFAR, along with dummy variable graduation years, is the only variable run in the first model specification (test #1) to get an idea of its predictive ability alone. The estimated impact of PFAR suggests that a one point increase in PFAR results in a .006 improvement in raw Primary flight grade (PFG). Another interpretation of this outcome is a one point higher PFAR raises PFG by seven percentile points (i.e. from the 51st to the 58th). As variables are added in subsequent tests the value of PFAR remains essentially the same. This result is interesting when considering how the value of AQR decreased in each test in the previous model. This outcome is possibly explained by the fact that the other variables in the model are not highly correlated with PFAR and therefore account for unique variance in the model.

OOM is added in test #3 and #4 and again, is negative and significant. The model shows that an increase of 100 places in OOM would result in a PFG increase of .005 or an increase of 5 percentile points (from the 51st percentile to the 56th).

In test #2 demographics are added. Both race variables are negative, however only the Other Race variable is statistically significant. An Asian American, Native American or "Other" is predicted to have a .043 point lower PFG. All other things being equal, a Caucasian would be expected to perform at 37 percentile points higher than someone classified as "Other Race" (14th to 51st). The coefficient for Other Race remains nearly the same throughout the subsequent tests. The female variable is positive but not significant, which coincides with what was found in the literature review that there was no statistical difference among genders in primary flight school grades (Reinhart, 1998).

2. Analysis Two – Alternate Variables

In this model, adding academic major information has no impact on the PFAR, OOM or CAQPR/CMQPR coefficients and actually reduces adjusted R^2 (from .115 to .113) when combined with OOM and when combined with CAQPR/CMQPR (.122 to .120). Less Technical majors and Humanities/Social Science majors are again predicted

to do less well than High Technical majors, though neither outcome is significant. This follows Reis' (2000) findings that academic major did not have a significant impact on the flying portion of primary and was an expected outcome of this study.

In test #4 academic and military grades are once again added to the model. Academic grades are found to be positive and significant. A one point higher CAQPR results in a PFG increase of .029 and an improvement of 30 percentile points (from the 51st to the 81st percentile). In this case, it seems that academic grades are predictive not necessarily because of their "academic nature," but simply because they demonstrate a performance measure. Military grades are not significant in this regression. These results agree with Reinhart's (1998) findings completely, that results of CMQPR were inconclusive but that CAQPR was directly related to primary flight grades. Likewise, Morales and Ree (1992) found cognitive ability to be a better predictor of training and flying performance that specific ability (job knowledge). This result flies in the face of the critics who claim no association between academic intelligence and job performance.

D. LOGISTIC REGRESSION ON ATTRITION

The third and final test is to determine which, if any, of the variables given, are the best predictors of attrition from flight school during or before the Primary phase of training. The same predictor variables that are used for the two linear regression models are used in the attrition model. Because of the coding of the dependant variable ("0" complete, "1" attrite) positive numbers indicate "more likely" to attrite, negative numbers indicate "less likely" to attrite. Table 3 shows some basic summary statistics for this model, as well as the marginal effects and their statistical significance.[20]

20 Marginal Effects are transformations of logit coefficients to unstandardized slope coefficients, evaluated at the mean levels of all independent variables.

Table 5. Logistic Regression on Attrition

	Analysis One			Analysis Two	
	Current Selection Method			Alternate Variables	
Predictor Variables	**test #1**	**test #2**	**test #3**	**test #4**	**test #5**
DEMOGRAPHICS					
female		-0.029	-0.020	-0.018	-0.018
African American		0.089/*	0.034	0.030	0.027
other race (a)		0.009	0.004	0.003	-0.001
class of 1996	0.014	0.020	0.012	0.013	0.011
class of 1997	0.048	0.050	0.031	0.031	0.033
class of 1998	0.072/**	0.079/**	0.056/*	0.059/**	0.056/**
ASTB					
Pilot Bio Inventory	-0.013	-0.011	-0.010	-0.006	-0.007
Order of Merit			0.0002/**	0.0002/**	
GRADES					
Academic grades					-0.091/**
Military Grades					-0.026
ACADEMIC MAJOR					
Humanities/Social Sci major				0.045/**	0.045/**
Less Tech major				0.019	0.018
Constant	-0.120/*	-0.137/*	-0.196/**	-0.222/**	0.210
a. Other non-Caucasian race besides African American. b. ** indicates statistically significant at p≤.01. c. * indicates statistically significant at p≤.05.					
SUMMARY STATISTICS:					
Model Chi sq	15.337/**	21.5/**	58.5/**	67.2/**	68.8/**
-2 log likelihood	525.9	519.8	482.7	474	472.4
pseudo R^2	0.037	0.051	0.137	0.157	0.161
cases	961	961	961	961	961
% cases correct class: 0	55.80%	63.60%	68.30%	67.20%	67.60%
1	65.40%	64.10%	71.80%	70.50%	73.10%
total	56.60%	63.70%	68.60%	67.40%	68.10%

As the table shows, the goodness of fit of the model improves through each test. The percentage of cases correctly classified to complete flight school through the primary stage increased from 56% in the first test to 68% in the last, while the cases correctly classified to attrite increased from 65% in the first test to 73% percent in the last, with the overall model increasing from 57% to 68%.

1. Analysis One - Pilot Biographical Inventory (PBI) and OOM

Prior to April 2002 this component of the ASTB was used to predict attrition due to flight or academic failure or Drop-On-Request during or before Primary. The test itself has not changed but there is no longer a minimum score requirement for PBI. It is included in the regression to conduct an independent test of its predictive power. Based on the decision to no longer include it in the requirement for qualification it was expected to be positive but not significant, and this in fact was the result of the model.

Order of Merit is added in test #3 and is found to be statistically significant. A 100 place improvement in Order of Merit results in a 2% less likely chance for attrition.

Demographic information is added in test #2. In test #2 and #3 African American is positive and significant (more likely to attrite), however it is no longer significant when additional variables are included. When combined only with academic major information and other demographic factors African Americans are predicted between 7.2% and 8.9% more likely to attrite. However when combined with ranking information (Order of Merit or academic/military grades) in tests #4 through #6 race is no longer significant, indicating that race in and of itself is not the cause for attrition, rather their academic grades or class standing.

The female variable was negative but not significant. This result was expected and is supported by Baisden's (1992) study that found differences in attrition rates not to be statistically significant, and Hafner's (2000) more recent study finding gender not to bea significant predictor of completing flight training.

2. Analysis Two – Alternate Variables

Academic grades, added in tests # 5, are positive and significant, and indicate that with a one point improvement in CAQPR, one would be 9.1% less likely to attrite. Military grades are negative and not significant. These results contradict Hafner's (2000) findings completely, that USNA graduates with higher CMQPRs were more likely to complete flight school training, and that academic grades were not a significant predictor of completion. These results would support Weeks (2000) assertion that using military performance as the strongest predictor of aviation assignment at the US Air Force Academy could, in fact, be contributing to the increased attrition in flight training.

Both Humanities/Social Sciences majors and Less Technical majors are predicted more likely to attrite, but only the results for HUMSS majors are significant. Depending on the combination of variables HUMSS majors are predicted to be between 4.5% and 6.8% more likely to attrite than High Technical majors. This supports Reis' (2000) results that non-engineers were more likely to attrite from flight school.

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V. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

A. INTRODUCTION

The first goal of this research is to test the criteria currently used for U.S. Naval Academy Service assignment against performance measures from naval pilot training and determine their predictive power. The second goal is to test alternate criteria available against the same performance measures, and determine whether or not the alternative criteria can better predict performance. Two seemingly different performance measures from flight school are used as benchmarks: final academic grades from Aviation Preflight Indoctrination and final flight grades from Primary phase. Additionally, attrition is examined to see which of the USNA criteria can accurately predict it.

It is expected that academic measures from USNA (OOM and CAQPR, predominantly, CMQPR to a somewhat lesser extent) as well as a highly technical major, will predict performance in API, because it is an academic setting and due to the technical nature of the classes. AQR is likewise expected to predict as has been previously proven. The same academic measures are expected to predict Primary flight grades, though to a lesser extent. PFAR is expected to predict as validated, and majors are not expected to predict. OOM and CMQPR are the only variables expected to be predictive of attrition, because they both represent measures of motivation.

B. SUMMARY AND CONCLUSIONS

In the first regression (on API grades) Order of Merit consistently has the highest standardized coefficients (absolute value, since OOM is actually negative) for the tests in which it is included, and CAQPR is a close second in the tests where it replaces OOM. The significant results for OOM and CAQPR are expected, however the degree in which OOM and CAQPR overwhelmed AQR are not. The standardized coefficients for OOM (-.408) and CAQPR (.416) are more than double the relative strength of AQR (.197/.168).

Perhaps the most interesting result is that of the grades in academic major interaction variables. The results show that CAQPR is a significant predictor for everyone, but as is indicated by the interaction, grades for HUMSS majors "matter"

above and beyond that of just the CAQPR variable. In other words, a one point higher CAQPR for a HUMSS major yields a greater difference in NASCRAW than for a Technical major, which is interesting, since HUMSS majors are predicted to do less well.

Ultimately, API is an academic setting, and expectedly an academic measure such as CAQPR and the 64% of OOM represented by academic grades are highly associated with API grades. Furthermore, API is rich in technical courses, making a highly technical major background a benefit. This result could be due to a High Technical major's past exposure to similar academic subjects, or perhaps could be explained by the type of person that selects a High Technical major, already having a propensity to interest and high performance in these types of technical academic settings. Less Technical major is negative but not significant, but as mentioned before, Humanities/Social Science major is negative and significant. This is interesting because even as a HUMSS major, a USNA graduate earns a Batchelor of Science degree because of the wealth of technical courses they are required to take above and beyond that of a HUMSS major at a civilian school.

For the test on Primary flight grades the results are similar. OOM and CAQPR are again the strongest predictors based on the standardized coefficient, to the extent that the standardized coefficients are over 150% that of PFAR (.111/.112 compared to .075/.067). Again, the test created and validated to be predictive of performance, represented by the PFAR, is positive and significant but not the strongest predictor. Academic major information is not significant in this test, alone or as an intervening variable combined with CAQPR.

It appears that in the case of flying, where there is not as clear an association between measures in college and performance in flight school, and with no available job samples, grades and class standing are again the strongest predictors. Though they have little to do with the actual stick-and-rudder aspect of flying, CAQPR and OOM are performance measures in their own right and in a way represent a drive to succeed as well as academic talent. This fact alone may cause the association. They do not have the impact they do in the case of API grades, but are positive and significant nonetheless.

The predictors for attrition do not vary much from the previous two tests. Once again, OOM and CAQPR are significant predictors with 2% less likelihood for attrition for 100 places higher in OOM, and 15.3% less likelihood for a 1 point higher CAQPR. Again, it seems that HUMSS majors are at a deficit with a greater likelihood for attrition ranging between 4.4% and 6.5%. Chapter three shows that people attrite for a myriad of reasons. With Drop-On-Request (DOR) and Flight failure as our sole focus in this study, it stands to reason that the same variables that explain poor performance would also explain attrition. Though students DOR for many reasons (loss of interest in flying, the program is not what was expected) a great many DOR because they find the program too difficult and/or know that flight failure is an eventuality.

This analysis examined variables available at the United States Naval Academy to determine performance in two flight school phases; one academic and one flying, as well as attrition from flight school. While these results indicate that the current method for selecting individuals for pilot flight school is certainly adequate, it is clear from the analysis that, in general, there are other variables that could better predict these outcomes.

The results are not the same for each regression, in fact when comparing the "current method" with an "alternate variables" the predictive power of each varies by regression. For the first regression (on API grades), the current method explains one third of the variation in the model (adjusted R^2 .325) compared to over 37% (adjusted R^2 .371) explained by the alternate variables. In the second regression (on Primary flight grades) the results were nearly equal for both methods (adjusted R^2 of .115 for current method compared to .122 for alternate variables). In the test on attrition, the pseudo R^2 for the current method is .137 while .161 for the alternate variables, and the percentage of cases correctly classified to attrite is also greater for the alternate variables, at 73.1% compared to 71.8% correctly classified for the current method.

These results show that "performance in flight school" is a very general criterion and to determine which variables will better predict performance, one must first decide which performance measure is desired. Though the specific variables that predict vary by test, it is clear that using more variables than just OOM, ASTB and an interview offer a more thorough picture of flight school performance. If predicting the entire package is

the goal, then in two tests of three (API and attrition) the alternate variables should be used and in the third (Primary flight grades) the results of both methods were the same. At no point does the current method of selection have a greater predictive impact than the alternate variables.

Another interesting and quite surprising result of this study is how the ASTB variables compare to the USNA variables in the regressions. One would expect that a test that has been created, validated and improved over the years to predict an outcome such as flight school performance would have more explanatory power than is the case in this analysis. In the first regression AQR is less than half the strength of OOM and CAQPR, and in the second, PFAR is only about two thirds the strength of OOM and CAQPR. The ASTB component for the third and final test, PBI, has previous to this study been removed as a requirement for qualification. The argument could be made that, with these other, stronger variables available, why go to the effort and expense of an additional test? While the OOM and CAQPR variables prove in this particular study to be stronger, the more variables that are available the better the predictive power of the overall model will be.

C. RECOMMENDATIONS

The author understands that because this test only includes pilot flight school, blanket statements/recommendations about the service assignment process in general cannot be made. The current method for assigning billets for other warfare specialties may already be the best available solution. Based on the results of this study the following recommendations are made:

1. Use CAPQR in place of OOM in the aviation service assignment multiple.
2. Include a weighted academic major variable that gives more points to High Technical majors. Because of the difficulty of their courses over that of Humanities/Social Sciences majors, High Technical majors may suffer lower CAQPR/OOMs as a result, to the extent that they may not otherwise be able to service assign pilot.
3. Leave the ASTB as is.

This study is designed to examine the service assignment process for the Naval Academy, but some of the results could clearly benefit midshipmen as well. Academic major selection may turn out differently if the students are made aware that Humanities/Social Science Majors are likely to perform lower in the academic portion of API as well as be more likely to attrite. With the "Poly Sci, QPR high, and fly" folklore that has long permeated the Brigade of Midshipmen, the truth of major selection impact on flight school performance may lead midshipmen to make different decisions with regards to academic major.

D. FUTURE RESEARCH

To make the service assignment process the best it can be, a similar test to this should be performed for all warfare areas. This thesis only makes recommendations in so far as what variables should be changed in the aviation service assignment multiple for pilots, additional research should be conducted to decide how best to allocate the ratio of weight for each variable of the multiple.

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APPENDIX A. API GRADES LINEAR REGRESSION – SPSS RESULTS

TEST #1

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	87.928	.537		163.617	.000
	AQR AQR	.928	.075	.369	12.305	.000
	YEAR96 GRADUATION YEAR-1996	-1.174	.304	-.144	-3.859	.000
	YEAR97 GRADUATION YEAR-1997	-1.485	.303	-.184	-4.898	.000
	YEAR98 GRADUATION YEAR-1998	-1.065	.322	-.122	-3.310	.001

TEST #2

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	88.366	.566		156.242	.000
	AQR AQR	.881	.078	.350	11.309	.000
	FEMALE FEMALE=1; MALE=0	-.801	.406	-.061	-1.971	.049
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=	-.603	.639	-.029	-.944	.346
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-.809	.414	-.059	-1.954	.051
	YEAR96 GRADUATION YEAR-1996	-1.171	.305	-.144	-3.839	.000
	YEAR97 GRADUATION YEAR-1997	-1.498	.303	-.185	-4.941	.000
	YEAR98 GRADUATION YEAR-1998	-1.022	.324	-.117	-3.151	.002

TEST #3

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	92.516	.577		160.368	.000
	AQR AQR	.624	.072	.248	8.680	.000
	FEMALE FEMALE=1; MALE=0	-1.115	.365	-.084	-3.052	.002
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=	.518	.578	.025	.897	.370
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-.354	.373	-.026	-.950	.343
	YEAR96 GRADUATION YEAR-1996	-.994	.274	-.122	-3.629	.000
	YEAR97 GRADUATION YEAR-1997	-1.161	.273	-.144	-4.255	.000
	YEAR98 GRADUATION YEAR-1998	-.687	.292	-.079	-2.357	.019
	OOM Order of Merit	-6.43E-03	.000	-.425	-15.118	.000

TEST #4

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	93.774	.615		152.497	.000
	AQR AQR	.496	.075	.197	6.645	.000
	FEMALE FEMALE=1; MALE=0	-1.210	.360	-.091	-3.356	.001
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=1	.549	.569	.026	.965	.335
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-.350	.367	-.025	-.955	.340
	YEAR96 GRADUATION YEAR-1996	-1.056	.271	-.130	-3.901	.000
	YEAR97 GRADUATION YEAR-1997	-1.152	.269	-.142	-4.289	.000
	YEAR98 GRADUATION YEAR-1998	-.765	.287	-.087	-2.661	.008
	HUMSS USNA MAJORS-HUMSS	-1.310	.232	-.169	-5.657	.000
	LESSTCH USNA MAJORS-EGE-SGS-SOC-SCS	-.490	.270	-.052	-1.815	.070
	OOM Order of Merit	-6.18E-03	.000	-.408	-14.611	.000

TEST #5

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	76.330	1.464		52.121	.000
	AQR AQR	.558	.072	.222	7.796	.000
	FEMALE FEMALE=1; MALE=0	-1.156	.360	-.087	-3.215	.001
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=	.607	.569	.029	1.067	.286
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-.371	.367	-.027	-1.010	.313
	YEAR96 GRADUATION YEAR-1996	-.970	.279	-.119	-3.475	.001
	YEAR97 GRADUATION YEAR-1997	-1.206	.283	-.149	-4.253	.000
	YEAR98 GRADUATION YEAR-1998	-.661	.307	-.076	-2.156	.031
	CAQPR Academic CQPR	3.540	.303	.410	11.665	.000
	CMQPR Military CQPR	1.047	.522	.072	2.006	.045

TEST #6

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	79.081	1.544		51.206	.000
	AQR AQR	.423	.074	.168	5.704	.000
	FEMALE FEMALE=1; MALE=0	-1.259	.354	-.095	-3.553	.000
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=	.656	.559	.031	1.172	.241
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-.377	.361	-.027	-1.046	.296
	YEAR96 GRADUATION YEAR-1996	-1.086	.276	-.134	-3.930	.000
	YEAR97 GRADUATION YEAR-1997	-1.263	.279	-.156	-4.522	.000
	YEAR98 GRADUATION YEAR-1998	-.822	.303	-.094	-2.714	.007
	HUMSS USNA MAJORS-HUMSS	-1.354	.229	-.174	-5.903	.000
	LESSTCH USNA MAJORS-EGE-SGS-SOC-SCS	-.479	.268	-.051	-1.787	.074
	CAQPR Academic CQPR	3.587	.298	.416	12.023	.000
	CMQPR Military CQPR	.614	.522	.042	1.177	.240

TEST #7

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	80.685	1.722		46.853	.000
	AQR AQR	.425	.074	.169	5.730	.000
	FEMALE FEMALE=1; MALE=0	-1.270	.354	-.096	-3.591	.000
	AFRAMER DUMMY VAR: AFRICAN AMERICAN	.731	.560	.035	1.304	.193
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-.358	.360	-.026	-.993	.321
	YEAR96 GRADUATION YEAR-1996	-1.074	.276	-.132	-3.891	.000
	YEAR97 GRADUATION YEAR-1997	-1.297	.279	-.160	-4.646	.000
	YEAR98 GRADUATION YEAR-1998	-.890	.304	-.102	-2.927	.004
	HUMSS USNA MAJORS-HUMSS	-4.912	1.596	-.633	-3.078	.002
	LESSTCH USNA MAJORS-EGE-SGS-SOC-SCS	-2.118	1.757	-.226	-1.206	.228
	CAQPR Academic CQPR	3.171	.364	.367	8.716	.000
	CMQPR Military CQPR	.514	.523	.035	.983	.326
	HMSSQPR HUM/SS Major CAQPR	1.215	.540	.454	2.251	.025
	LSTCHQPR Less Technical Major CAQPR	.546	.598	.168	.912	.362

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APPENDIX B. PRIMARY FLIGHT GRADES LINEAR REGRESSION – SPSS RESULTS

TEST #1

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.031	.016		189.439	.000
	PFAR PFAR	6.376E-03	.002	.085	2.709	.007
	YEAR96 GRADUATION YEAR-1996	-2.32E-02	.009	-.097	-2.482	.013
	YEAR97 GRADUATION YEAR-1997	-4.41E-02	.009	-.184	-4.701	.000
	YEAR98 GRADUATION YEAR-1998	-9.08E-02	.010	-.347	-9.062	.000

TEST #2

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.033	.017		182.306	.000
	PFAR PFAR	6.664E-03	.002	.089	2.767	.006
	FEMALE FEMALE=1; MALE=0	1.459E-02	.012	.038	1.171	.242
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=1	-1.76E-02	.020	-.028	-.892	.373
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-4.33E-02	.013	-.105	-3.358	.001
	YEAR96 GRADUATION YEAR-1996	-2.46E-02	.009	-.103	-2.637	.009
	YEAR97 GRADUATION YEAR-1997	-4.62E-02	.009	-.193	-4.941	.000
	YEAR98 GRADUATION YEAR-1998	-9.30E-02	.010	-.355	-9.237	.000

TEST #3

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.059	.018		169.083	.000
	PFAR PFAR	5.633E-03	.002	.075	2.335	.020
	FEMALE FEMALE=1; MALE=0	1.389E-02	.012	.036	1.121	.263
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=1	-7.01E-03	.020	-.011	-.353	.724
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-3.95E-02	.013	-.096	-3.071	.002
	YEAR96 GRADUATION YEAR-1996	-2.35E-02	.009	-.098	-2.525	.012
	YEAR97 GRADUATION YEAR-1997	-4.40E-02	.009	-.183	-4.715	.000
	YEAR98 GRADUATION YEAR-1998	-9.05E-02	.010	-.345	-9.020	.000
	OOM Order of Merit	-4.99E-05	.000	-.111	-3.472	.001

TEST #4

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.062	.019		160.521	.000
	PFAR PFAR	5.344E-03	.002	.071	2.154	.031
	FEMALE FEMALE=1; MALE=0	1.377E-02	.012	.036	1.108	.268
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=	-6.59E-03	.020	-.011	-.332	.740
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-3.94E-02	.013	-.096	-3.063	.002
	YEAR96 GRADUATION YEAR-1996	-2.37E-02	.009	-.099	-2.540	.011
	YEAR97 GRADUATION YEAR-1997	-4.40E-02	.009	-.183	-4.709	.000
	YEAR98 GRADUATION YEAR-1998	-9.07E-02	.010	-.346	-9.022	.000
	HUMSS USNA MAJORS-HUMSS	-4.21E-03	.008	-.018	-.532	.595
	LESSTCH USNA MAJORS-EGE-SGS-SOC-SCS	-1.64E-03	.009	-.006	-.175	.861
	OOM Order of Merit	-4.86E-05	.000	-.108	-3.322	.001

TEST #5

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.889	.051		56.310	.000
	PFAR PFAR	5.037E-03	.002	.067	2.088	.037
	FEMALE FEMALE=1; MALE=0	1.363E-02	.012	.035	1.104	.270
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=1	-3.96E-03	.020	-.006	-.200	.841
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-3.85E-02	.013	-.094	-3.004	.003
	YEAR96 GRADUATION YEAR-1996	-2.16E-02	.010	-.090	-2.251	.025
	YEAR97 GRADUATION YEAR-1997	-4.22E-02	.010	-.176	-4.307	.000
	YEAR98 GRADUATION YEAR-1998	-8.75E-02	.011	-.334	-8.173	.000
	CAQPR Academic CQPR	2.860E-02	.010	.112	2.769	.006
	CMQPR Military CQPR	2.012E-02	.018	.046	1.107	.269

TEST #6

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.892	.055		52.725	.000
	PFAR PFAR	4.890E-03	.002	.065	1.972	.049
	FEMALE FEMALE=1; MALE=0	1.340E-02	.012	.035	1.082	.280
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=	-3.79E-03	.020	-.006	-.191	.848
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-3.85E-02	.013	-.094	-3.000	.003
	YEAR96 GRADUATION YEAR-1996	-2.16E-02	.010	-.091	-2.239	.025
	YEAR97 GRADUATION YEAR-1997	-4.22E-02	.010	-.176	-4.299	.000
	YEAR98 GRADUATION YEAR-1998	-8.77E-02	.011	-.334	-8.141	.000
	HUMSS USNA MAJORS-HUMSS	-2.53E-03	.008	-.011	-.319	.750
	LESSTCH USNA MAJORS-EGE-SGS-SOC-SCS	7.484E-04	.009	.003	.079	.937
	CAQPR Academic CQPR	2.854E-02	.010	.111	2.760	.006
	CMQPR Military CQPR	1.962E-02	.019	.045	1.060	.290

TEST #7

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.871	.061		46.942	.000
	PFAR PFAR	4.859E-03	.002	.065	1.958	.051
	FEMALE FEMALE=1; MALE=0	1.347E-02	.012	.035	1.087	.277
	AFRAMER DUMMY VAR: AFRICAN AMERICAN=1	-4.99E-03	.020	-.008	-.251	.802
	OTHRACE DUMMY VAR: OTHER MINORITY=1	-3.87E-02	.013	-.094	-3.011	.003
	YEAR96 GRADUATION YEAR-1996	-2.18E-02	.010	-.091	-2.248	.025
	YEAR97 GRADUATION YEAR-1997	-4.17E-02	.010	-.174	-4.238	.000
	YEAR98 GRADUATION YEAR-1998	-8.67E-02	.011	-.331	-8.006	.000
	HUMSS USNA MAJORS-HUMSS	4.686E-02	.058	.204	.815	.415
	LESSTCH USNA MAJORS-EGE-SGS-SOC-SCS	1.962E-02	.063	.071	.313	.755
	CAQPR Academic CQPR	3.388E-02	.013	.132	2.675	.008
	CMQPR Military CQPR	2.101E-02	.019	.048	1.130	.259
	HMSSQPR HUM/SS Major CAQPR	-1.69E-02	.019	-.213	-.867	.386
	LSTCHQPR Less Technical Major CAQPR	-6.21E-03	.021	-.065	-.292	.771

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APPENDIX C. ATTRITION LOGISTIC REGRESSION – SPSS RESULTS

TEST #1

VARIABLE	XBAR	LOGIT	X*LOGIT	MARGINAL LOGIT*P(1-P)
PBI	7	-0.1804	-1.262799	-0.013225029
YEAR96	0.27	0.189743	0.0512306	0.013909975
YEAR97	0.28	0.649251	0.1817904	0.047596305
YEAR98	0.22	0.977075	0.2149564	0.07162887
Constant	1	-1.63223	-1.632231	-0.119658066

TEST #2

VARIABLE	XBAR	LOGIT	X*LOGIT	MARGINAL LOGIT*P(1-P)
PBI	7	-0.15472	-1.083027	-0.011043892
FEMALE	0.081	-0.40348	-0.032682	-0.02880097
AFRAMER	0.03	1.245171	0.0373551	0.088881204
OTHRACE	0.04	0.128435	0.0051374	0.009167777
YEAR96	0.27	0.283601	0.0765723	0.020243656
YEAR97	0.28	0.701087	0.1963043	0.050044102
YEAR98	0.22	1.105156	0.2431343	0.078886853
Constant	1	-1.92148	-1.921476	-0.137156378

TEST #3

VARIABLE	XBAR	LOGIT	X*LOGIT	MARGINAL LOGIT*P(1-P)
PBI	7	-0.16453	-1.151729	-0.009526818
FEMALE	0.081	-0.35238	-0.028543	-0.020403519
AFRAMER	0.03	0.595711	0.0178713	0.034493026
OTHRACE	0.04	0.070519	0.0028208	0.004083205
YEAR96	0.27	0.215001	0.0580503	0.012449058
YEAR97	0.28	0.532916	0.1492164	0.030857041
YEAR98	0.22	0.960546	0.21132	0.055617789
OOM	431	0.003265	1.4071896	0.000189048
Constant	1	-3.3878	-3.387802	-0.196161504

TEST #4

VARIABLE	XBAR	LOGIT	X*LOGIT	MARGINAL LOGIT*P(1-P)
PBI	7	-0.11066	-0.774614	-0.005927898
FEMALE	0.081	-0.34203	-0.027704	-0.01832207
AFRAMER	0.03	0.558069	0.0167421	0.02989517
OTHRACE	0.04	0.049139	0.0019656	0.002632344
YEAR96	0.27	0.249997	0.0674992	0.013392085
YEAR97	0.28	0.58445	0.1636459	0.031308357
YEAR98	0.22	1.094362	0.2407596	0.058623808
HUMSS	0.32	0.844157	0.2701303	0.045220608
LESSTCH	0.18	0.361089	0.0649961	0.019343174
OOM	431	0.003052	1.315546	0.000163509
Constant	1	-4.14881	-4.148809	-0.222247359

TEST #5

VARIABLE	XBAR	LOGIT	X*LOGIT	MARGINAL LOGIT*P(1-P)
PBI	7	-0.13274	-0.92921	-0.007076154
FEMALE	0.081	-0.33618	-0.027231	-0.017920753
AFRAMER	0.03	0.508966	0.015269	0.027131285
OTHRACE	0.04	-0.02218	-0.000887	-0.001182381
YEAR96	0.27	0.212368	0.0573394	0.011320643
YEAR97	0.28	0.620316	0.1736884	0.03306696
YEAR98	0.22	1.058834	0.2329435	0.056442892
HUMSS	0.32	0.850398	0.2721273	0.045331855
LESSTCH	0.18	0.334448	0.0602006	0.017828304
CAQPR	2.93	-1.7032	-4.99039	-0.090792144
CMQPR	3.28	-0.49369	-1.619316	-0.026317163
Constant	1	3.940087	3.9400868	0.210032826

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